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THESIS

IMPROVING NAVY RECRUITING WITH THE NEW PLANNED RESOURCE OPTIMIZATION MODEL WITH EXPERIMENTAL DESIGN (PROM-WED)

by

Allison R. Hogarth

March 2017

Thesis Advisor:	Thomas Lucas
Co-Advisor:	Connor McLemore
Second Reader:	Paul Sanchez

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13. ABSTRACT (maximum 200 words)

The Navy spends over $300 million per year to recruit approximately 35,000 new active duty enlisted Sailors. The Navy has historically used a non-linear optimization model, the Planned Resource Optimization (PRO) model, to help inform decisions on the allocation of those recruiting resources. Input variables to the PRO model include economic influences and policy factors. The result is a recommended allocation of resources for advertisements, recruiters, enlistment bonuses, and education incentives. The PRO model's primary limitations are (1) potential deviations of input variables are not taken into consideration, and (2) extensive experimentation is not feasible. Realistically, input variables to the PRO model fluctuate, are unpredictable, and can interact with other variables to influence the recruiting environment and affect the optimal allocation of recruiting resources. This paper describes the "Planned Resource Optimization Model with Experimental Design" (PROM-WED), a tool that alleviates the limitations and enhances the analytic utility of the legacy PRO model. PROM-WED embeds the legacy PRO model within a data farming environment. PROM-WED's graphical user interface and decision support capability provide decision makers with robust insights into variable interactions and uncertainties to better inform their recruiting resourcing decisions.

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IMPROVING NAVY RECRUITING WITH THE NEW PLANNED RESOURCE OPTIMIZATION MODEL WITH EXPERIMENTAL DESIGN (PROM-WED)

Allison R. Hogarth
Lieutenant, United States Navy
B.S., The George Washington University, 2012

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March 2017

Approved by: Thomas Lucas
Thesis Advisor

Connor McLemore
Co-Advisor

Paul Sanchez
Second Reader

Patricia Jacobs
Chair, Department of Operations Research

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ABSTRACT

The Navy spends over $300 million per year to recruit approximately 35,000 new active duty enlisted Sailors. The Navy has historically used a non-linear optimization model, the Planned Resource Optimization (PRO) model, to help inform decisions on the allocation of those recruiting resources. Input variables to the PRO model include economic influences and policy factors. The result is a recommended allocation of resources for advertisements, recruiters, enlistment bonuses, and education incentives. The PRO model's primary limitations are (1) potential deviations of input variables are not taken into consideration, and (2) extensive experimentation is not feasible. Realistically, input variables to the PRO model fluctuate, are unpredictable, and can interact with other variables to influence the recruiting environment and affect the optimal allocation of recruiting resources. This paper describes the "Planned Resource Optimization Model with Experimental Design" (PROM-WED), a tool that alleviates the limitations and enhances the analytic utility of the legacy PRO model. PROM-WED embeds the legacy PRO model within a data farming environment. PROM-WED's graphical user interface and decision support capability provide decision makers with robust insights into variable interactions and uncertainties to better inform their recruiting resourcing decisions.

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LIST OF ACRONYMS AND ABBREVIATIONS

AFQT	Armed Forces Qualification Test
ASVAB	Armed Services Vocational Aptitude Battery
AVF	all-volunteer force
CPT	cost-performance tradeoff
DOD	Department of Defense
DOE	design of experiments
EB	enlistment bonus
FY	fiscal year
GAO	Government Accountability Office
GED	general educational development
GUI	graphical user interface
HumRRO	Human Resources Research Organization
JPM	Job Performance Measurement/Enlistment Standards
LRP	loan repayment program
MEU	Marine Expeditionary Unit
MIP	mixed integer program
MPT&E	Manpower, Personnel, Training and Education
N1	Deputy Chief of Naval Operations for Manpower, Personnel, Training and Education
NCF	Navy college fund
NCO	new contract objective
NEC	Navy enlisted classification
NF	nuclear field
NOLH	nearly orthogonal Latin hypercube
NOS	Navy occupational specialties
NPS	Naval Postgraduate School
NRC	Navy Recruiting Command
OSAM	Officer Strategic Analysis Model
OSD	Office of the Secretary of Defense
PC	personal computer

POM	program objective memorandum
POR	program of record
PPBE	Planning, Programming, Budget and Execution
PRO	Planned Resource Optimization
PROM-WED	Planned Resource Optimization with Experimental Design
QMA	qualified military available
SEAL	sea, air and land
SEED	Simulation Experiments & Efficient Designs
STORM	Synthetic Theater Operations Research Model
TSC	Test Score Category
UE	unemployment rate
VBA	Visual Basic for Applications

EXECUTIVE SUMMARY

The mission of the United States Navy is “to maintain, train and equip combat-ready Naval forces capable of winning wars, deterring aggression and maintaining freedom of the seas” (United States Navy, n.d.-b). Congress authorizes the Navy to maintain a force-strength of over 300,000 active duty personnel to execute this mission (Government Accountability Office, 2016, p. 5). The Navy spends over $300 million to recruit approximately 35,000 new active duty enlisted Sailors each year to sustain its manning strength (Department of the Navy, 2015, p. 7). Under the Deputy Chief of Naval Operations for Manpower, Personnel, Training and Education (N1/MPT&E), analysts use mathematical models to support decision makers on personnel and budget related resourcing issues (United States Navy, n.d.-a). One model that N1 has historically used to inform recruiting resourcing decisions is the Planned Resource Optimization (PRO) model.

The PRO model is a deterministic non-linear optimization model that provides users with a recommended set of resources to minimize the cost of Navy recruiting (Green & Mavor, 1994). The PRO model optimizes resources allocated to advertisements, enlistment bonuses, education incentives, and recruiters. Input variables to the model include economic influences such as unemployment rate and policy factors such as percentage of high quality recruits (Navy Recruiting Command, 2007). Limitations of the PRO model are (1) potential deviations of input variables are not taken into consideration, and (2) extensive experimentation is not feasible. Realistically, the input variables to the PRO model fluctuate, are unpredictable, and can interact with other variables to influence the recruiting environment and affect the optimal allocation of recruiting resources.

To alleviate the limitations and enhance the analytic utility of the legacy PRO model, we developed the “Planned Resource Optimization Model with Experimental Design” (PROM-WED). PROM-WED embeds the legacy PRO

model within a data farming environment. The foundation of PROM-WED's data farming wrapper is the nearly orthogonal Latin hypercube (NOLH). The NOLH design of experiments (DOE) builds experimental designs that efficiently and effectively explore the solution space (Cioppa & Lucas, 2007). This good space-filling capability means that uncertainties and fluctuations in input variables along with multivariable interactions can be adequately investigated (Sanchez & Wan, 2015).

The 33 and 129 design point NOLH designs were used to construct PROM-WED's data farming wrapper. The 33-point NOLH DOE tests each variable at 33 levels and grows data for 33 legacy PRO model runs, whereas the 129-point NOLH DOE tests each variable at 129 levels and grows data for 129 legacy PRO model runs. PROM-WED's graphical user interface (GUI) allows users to easily input a range of values for each input variable into the NOLH DOE worksheet, without need for knowledge or familiarity with data farming or DOE techniques (Sanchez, 2011).

A completed PROM-WED excursion grows a data set for either 33 or 129 data points. Automatically generated sensitivity analysis provides users with a basic risk assessment picture focused on the decision variables using the data grown by PROM-WED. Further insights into variable interactions and effects of input variables can be easily explored using available data analysis software. PROM-WED transforms the legacy PRO model into a resource that N1 can use to gain robust insights into the optimal allocation of recruiting resources.

A scenario of interest to N1 was run and analyzed using PROM-WED. Insights gained include:

1. To optimize the allocation of recruiting resources in fiscal year 2020, it is recommended that less funds be allocated to recruiters and more funds be allocated to enlistment bonuses and advertisements.
2. Advertising is the most influential decision variable. Over 80 percent of the total cost of recruiting variance is explained by changes in the recommended allocation of resources to advertising.

3. Once relative pay exceeds approximately 1.00, changes in the new accession mission have little to no effect on the recommended amount of resources allocated to advertising.

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I. INTRODUCTION

The mission of the United States Navy is “to maintain, train and equip combat-ready Naval forces capable of winning wars, deterring aggression and maintaining freedom of the seas” (United States Navy, n.d.-b). Under Title 10 of the United States Code, Congress authorizes the Navy to maintain a force-strength of over 300,000 active duty personnel to execute this mission (Government Accountability Office [GAO], 2016, p. 5). Each year, the Navy recruits approximately 35,000 new active duty enlisted Sailors to sustain this manning strength (Department of the Navy, 2015, p. 7). The Deputy Chief of Naval Operations for Manpower, Personnel, Training and Education (MPT&E/N1) is delegated with the responsibility over all Navy manpower readiness matters, to include recruiting (United States Navy, n.d.-a).

Analysts at N1 use mathematical models and simulations to support decision makers in the MPT&E domain during the Planning, Programming, Budget and Execution (PPBE) process. The PPBE process is the Department of Defense’s (DOD) “primary resource management system… for all appropriated funding” (Tomasini, n.d.). The DOD’s strategy, force structure, and allocation of resources are all delineated within the annual PPBE process (Tomasini, n.d.). Each year during the programming phase, N1 submits Program Objective Memorandum (POM) inputs, recommending how funds should be allocated within the Navy’s MPT&E domain (Defense Acquisition University [DAU], 2013, p. 4).

N1 has historically used the Planned Resource Optimization (PRO) model to inform decisions regarding the allocation of recruiting resources and estimate total recruiting costs. The PRO model is a deterministic, non-linear optimization model that provides users with a recommended set of resources that minimizes the cost of recruiting in order to achieve a given recruiting mission. The PRO model can also be used to estimate recruiting capacity for a given level of resources.

The PRO model is built in Microsoft Excel using both worksheet functions and Visual Basic for Applications (VBA) code. The PRO model's primary function is to provide a broad, estimated budget picture of Navy recruiting resource allocation in support of the POM. The PRO model is also used to answer questions such as, "what is the least expensive way to meet a recruiting mission?" and "how much money do we need to allocate for advertising to meet a given accession mission?" (Hogarth, Lucas, & McLemore, 2016, p. 3576)

A. PROBLEM STATEMENT

Recruiting a high quality all-volunteer force (AVF) is expensive. The Navy requires a growing number of high quality recruits to meet the needs of its technologically advanced fleet. In a perfect world, N1 would be given a blank check to cover the cost of recruiting a 100 percent high quality force. However, in reality, N1 faces a fiscally constrained environment.

The PRO model is a deterministic, non-linear optimization model that provides users with a recommended set of resources that attempts to minimize the cost of recruiting (Green & Mavor, 1994). Analysts at N1 use the PRO model to optimize resources allocated to advertisements, enlistment bonuses, education incentives, and recruiters. Input variables include economic influences such as unemployment rate, and policy factors such as target percentage of high quality recruits (Navy Recruiting Command, 2007). The PRO model's primary limitations are (1) deviations of input variables are not taken into consideration, and (2) extensive experimentation capability is not available. Realistically, the input variables to the PRO model fluctuate, are unpredictable, and can interact with other variables to influence the recruiting environment and affect the optimal allocation of recruiting resources.

B. THESIS PURPOSE

The objective of this research is to develop a tool that transforms the PRO model into a tool that provides N1 analysts with a robust decision support capability for recruiting resourcing decisions. In this research, the author wrapped

a design of experiments (DOE) capability around the legacy PRO model. We call the enhanced tool the Planned Resource Optimization Model with Experimental Design (PROM-WED).

The data farming wrapper in PROM-WED provides legacy PRO model users with the ability to input a range of possible values for input and decision variables. The legacy PRO model is run over each scenario that is formulated by the DOE tool. Instead of a single, discrete solution found by the legacy PRO model, PROM-WED grows data that gives robust insight into cause and effect relationships amongst the variables.

C. RESEARCH QUESTIONS

In order to best provide N1 analysts with a tool that improves their decision support analysis for recruiting budget estimates and resource allocation, this research is guided by the following questions:

1. How can design of experiment techniques better inform decision maker's determination of the optimal and robust combination of recruiting resources?
2. How can efficient design of experiment techniques be incorporated around the PRO model for future, on-the-spot risk and sensitivity analysis?
3. Can an enhanced PRO model give decision-makers a robust solution for the optimal allocation of recruiting resources?

D. METHODOLOGY

PROM-WED's data farming wrapper uses the Nearly Orthogonal Latin Hypercube (NOLH) DOE worksheet tool developed by the Simulation Experiments & Efficient Designs (SEED) Center for Data Farming at the Naval Postgraduate School (NPS), see https://harvest.nps.edu. A new graphical user interface (GUI) allows the user to input a range of values for each input variable into the NOLH DOE worksheet. The NOLH DOE worksheet was embedded into the PRO model. The user has the option to run an excursion using a 33-point design or a 129-point design. PROM-WED generates a robust recommended

allocation of recruiting resources. Basic sensitivity analysis provides the user with a risk assessment picture, and further analysis can be completed using any data analysis software package, such as JMP. Scenarios of interest to N1 are run and analyzed.

E. BENEFITS OF RESEARCH

The ability to quickly explore scenarios with a deterministic optimization model using efficient DOE techniques provides N1 with richer insights into combinations of resources that can be utilized to achieve a given active enlisted recruiting mission. Instead of a discrete expected value, the implementation of efficient DOE techniques provides decision-makers with a “robust [foundation to make] decisions or policies” (Sanchez, Sanchez, & Wan, 2014, p. 1). DOE methods will also provide improved insight into tradeoff relationships between input parameters and the output results (Vieira, Sanchez, Kienitz, & Belderrain, 2013, p. 264). N1 will also benefit from this study by gaining a tool that provides on-the-spot sensitivity analysis using sophisticated DOE techniques.

F. ORGANIZATION OF THESIS

This thesis is comprised of five chapters. Chapter I focuses on the motivation of the thesis and explains how the research questions are addressed. Chapter II discusses the history and composition of the PRO model and considers other research that has been done on military recruiting resource allocation and the implementation of data farming on simulation models. Chapter III addresses the methodology used to build PROM-WED, including a review of DOE techniques, and the components of PROM-WED. Chapter IV introduces scenarios of interest to N1, and the remainder of the chapter provides an analysis of the data generated for these scenarios using PROM-WED. Last, Chapter V provides concluding remarks, and recommendations for further work.

II. BACKGROUND

In this chapter, research on military recruiting resource allocation is presented, followed by a conceptual overview of the PRO model.

A. LITERATURE REVIEW

All military branches face the challenge of determining the best way to allocate recruiting resources. PRO is a model that the Navy has historically used to help decision makers gain insight to answer this question.

1. Recruiting Resource Allocation Models

Following the United States withdrawal from the Vietnam War in 1973, Congress terminated conscription, and the military transitioned to an All-Volunteer Force (AVF) (Morey & McCann, 1980, p. 1198). Critics of an AVF were concerned that it would result in weakened national security due to low quality recruits and insufficient accession numbers. In contrast to a military manned by conscripts, an AVF forced each service to expend more effort "to meet the various quantity and quality goals" for recruiting new enlistees (Morey & McCann, 1980, p. 1198). Various modeling efforts were made to gain insight into how to best allocate recruiting resources to meet the service's set recruiting goals.

In 1978, Chappell and Peel developed static and dynamic optimization models to determine the optimal allocation of advertising resources to achieve military recruiting goals. The dynamic model they developed introduced economic factors such as labor supply and incorporated current and past recruiting data to determine an optimal allocation of advertising resources (Chappell & Peel, 1978, p. 910).

In 1980, Morey and McCann developed a model to determine the optimal allocation of recruiting resources by inputting econometric data of a given region and descriptive data that reflects its demographic population. The model was conducive to "perform[ing] sensitivity analyses related to the impacts" of various

economic and demographic changes. Their model identified the percentage of recruits who graduated from high school as the indicator for recruit quality (Morey & McCann, 1980, p. 1204).

2. Cost-Performance Tradeoff Model

AVF concerns peaked in 1980, particularly in regards to how the military gauged recruit quality (Green & Mavor, 1994, p. 8). The DOD informed Congress that the Armed Services Vocational Aptitude Battery (ASVAB), the examination used to determine enlistment eligibility, was incorrectly scored between 1976 and 1980 (Green & Mavor, 1994, p. 2). This error resulted in hundreds of thousands of people entering military service who did not meet enlistment standards (Green & Mavor, 1994, p. 2).

Clinical psychologists advised that the recruits who did not meet minimum enlistment standards were classified as individuals who "generally need intense supervision and guidance, particularly under conditions of serious stress" (Laurence & Ramsberger, 1991, p. 8). These attributes are undesirable for military service.

In reaction to this mistake, Congress tasked the DOD "to link enlistment standards to job performance" (Green & Mavor, 1994, p. 2). This initiated the Joint-Service Job Performance Measurement/Enlistment Standards (JPM) Project. The first phase of the JPM project "concentrated on developing a variety of measures of job performance so that enlistment standards could be related to something close to actual performance on the job" (Green & Mavor, 1994, p. 7).

Following decades of research, phase one of the JPM project validated the ASVAB as "a reasonably valid predictor for performance in entry-level military jobs" (Green & Mavor, 1994, p. 10). High school graduation became an indicator of likelihood of first term enlistment completion. The military services now faced the challenge of determining "how much quality can we afford?" since "high-quality personnel cost more to recruit, and the public purse is not bottomless" (Green & Mavor, 1994, p. 4,10-11). The goal of the second phase of the JPM

project was to address this question. The cost-performance tradeoff (CPT) model was their solution (Green & Mavor, 1994, p. 11).

The CPT model is a tool that decision makers use to estimate the "probable effects on performance and/or costs of various scenarios" (Green & Mavor, 1994, p. 11). The CPT model is comprised of "four primary components: (1) the performance equations, (2) the recruiting cost function, (3) survival rates, and (4) training and compensation costs" (McCloy at al.,1992, p. iii). The PRO model is based upon the recruiting cost function, which is covered in the next section.

B. PLANNED RESOURCE OPTIMIZATION MODEL

The PRO model is a non-linear optimization model implemented in Microsoft Excel using both worksheet functions and VBA code. It evaluates user driven input variables over a recruiting cost function. The result is a recommended combination of recruiting resources to meet a given recruiting mission.

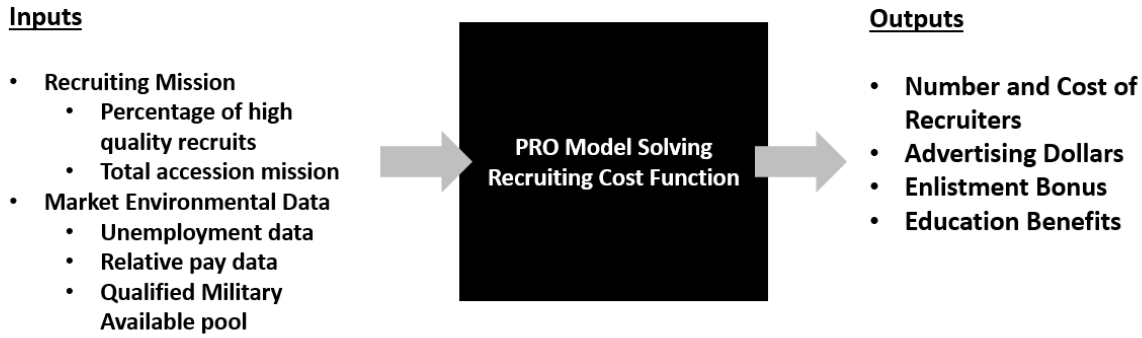
1. Components of the PRO Model

The PRO model uses the recruiting cost function from the CPT model to allocate recruiting resources while minimizing the cost of recruiting. A general review of the PRO model's conceptual framework and an overview of the workings of the PRO model follow.

a. Conceptual Framework

Input variables to the PRO model include decision variables, market factors, and policy factors that affect the cost and nature of recruiting. Users can change these inputs to test different recruiting scenarios. Figure 1 shows a conceptual representation of the PRO model.

Figure 1. Conceptual Representation of the PRO Model



Adapted from Navy Recruiting Command (2007, p. 5).

A PRO model excursion produces a point solution that tells the user how many production recruiters should be in the field along with the allocation of funds towards enlistment bonuses, education incentives, and advertisements. An example output of a PRO model excursion is shown in Figure 2.

Figure 2. PRO Model Output

	Resource Run	2015	2016	2017	2018	2019	2020	2021
	NCO	35,025	36,425	36,800	35,800	35,225	34,650	34,650
	Capacity	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Unemployment (%)	4.0	4.0	4.0	4.0	4.0	4.0	4.0
Float	Total Recruiters	4,092	4,632	4,608	4,315	4,106	3,945	3,923
	Total Recruiter Cost ($M)	$335.138	$383.495	$387.265	$368.083	$355.535	$347.480	$351.645
Float	Advertising ($M)	$86.203	$105.531	$105.352	$97.179	$91.278	$87.362	$87.981
Fixed	Enlistment Bonus ($M)	$40.971	$36.580	$41.340	$40.650	$42.230	$42.060	$42.810
Float	Education Incentives ($M)	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000
	LRP ($M)	$7.440	$11.220	$11.280	$11.380	$11.430	$11.460	$11.670
	HSDG	95%	95%	95%	95%	95%	95%	95%
	TSC I-IIIA	70%	70%	70%	70%	70%	70%	70%
	Total Cost ($M)	$469.752	$536.826	$545.236	$517.292	$500.473	$488.361	$494.106

Program Objective Memorandum (POM) FY17 version of the PRO model.

The interpretation of the point solution for fiscal year (FY) 2015 in Figure 2 is: *To meet an accession mission of 35,025 new Navy recruits with a fixed enlistment bonus budget of $40,971,000, the Navy should allocate 4,092 Sailors to recruiting duty and $86,203,000 to advertising.*

b. The Recruiting Cost Function

The recruiting cost function is "the underpinning of the [PRO] model" (Navy Recruiting Command, 2007, p. 6). The black box shown previously in Figure 1 represents the recruiting cost function. Users cannot alter the recruiting cost function to include the elasticities or pre-set data that feed into it.

The recruiting cost function provides the "minimum cost budget" recommended to recruit "a specified number of individuals" while taking into consideration the conditions of the "recruiting market" (Green & Mavor, 1994, p. 126–127). Enlistment supply functions and a constrained minimization problem are both critical components of the recruiting cost function (Green & Mavor, 1994, p. 126–127).

The variables of interest that build the recruiting cost function include (Green & Mavor, 1994, p. 126–127; Katznelson, 2010, p. 4; Navy Recruiting Command, 2007, p. 8.):

$H = High\ quality\ recruits$
$M = Medium\ quality\ recruits$
$L = Low\ quality\ recruits$
$C^q = Number\ of\ contracts\ signed\ in\ a\ given\ year, where\ q = H, M, L$
$C_0^q = Constant\ (calculated\ using\ base\ year\ knowns), where\ q = H, M, L$
$C_*^q = Minimum\ cost\ to\ contract\ given\ number\ of\ recruits, where\ q = H, M, L$
$\lambda_q = Lagrangian\ multiplier, where\ q = H, M, L$
$\alpha = Elasticity\ describing\ the\ relationship\ between\ the\ paramter\ and\ C^H$
$R^q = Number\ of\ production\ recruiters\ to\ recruit\ a\ given\ quality, where\ q = H, M, L$
$AD = Advertising\ dollars\ spent\ in\ the\ model\ year\ (inflation - adjusted\ to\ base\ year)$
$B = Average\ enlistment\ bonus\ paid\ to\ q = H\ (model\ year)$
$E = Average\ education\ benefits\ paid\ to\ q = H\ (model\ year)$
$v = Price\ index\ to\ deflate\ B\ and\ E\ into\ base\ year\ dollars$
$F = Factors\ affecting\ the\ recruiting\ market\ (i.e., unemployment, relative\ pay)$
$T = Testing\ cost$
$O = Fixed\ costs\ of\ recruiting$

The enlistment supply functions, shown in Figure 3, are separated into high, medium, and low quality categories of new accessions. These equations determine the expected number of recruits in each category that will be contracted per year (Green & Mavor, 1994, p. 126).

Figure 3. Enlistment Supply Functions

$$High\ Quality\ Contracts:$$
$$\ln(C^H) = \ln(C_o^H) + \alpha_R^H \ln(R^H) + \alpha_{AD} \ln(R^H) + \alpha_B ln\left(\frac{B}{v}\right) + \alpha_E ln\left(\frac{E}{v}\right) + \alpha_F \ln(F)$$

$$Medium\ Quality\ Contracts:$$
$$\ln(C^M) = \ln(C_o^M) + \alpha_R^M \ln(R^M) + \alpha_F \ln(F)$$

$$Low\ Quality\ Contracts:$$
$$\ln(C^L) = \ln(C_o^L) + \alpha_R^L \ln(R^L) + \alpha_F \ln(F)$$

Adapted from Green & Mavor, 1994, p.126; Navy Recruiting Command (2007, p. 8).

The “Navy Recruiting Cost Model User Manual” refers to the enlistment supply functions as recruiting cost functions (Navy Recruiting Command, 2007, p.8). Smith and Hogan refer to these functions as the enlistment supply functions in “Modeling Cost and Performance for Military Enlistment, Report of a Workshop” (Green & Mavor, 1994, p.126). For the purpose of this research, the functions shown in Figure 3 are referred to as enlistment supply functions.

The objective function shown in Figure 4 determines “the levels of recruiting resources and incentives required to recruit the specified mission at minimum cost” (Green & Mavor, 1994, p. 127).

Figure 4. Recruiting Cost Minimization Problem

$$Min[p^R(R^H + R^M + R^L) + p^{AD}AD + C_*^H(B + E) + T(C_*^H + C_*^M + C_*^L) + O]$$
$$-\lambda_H[C^H + C_*^H] - \lambda_M[C^M - C_*^M] - \lambda_L[C^L - C_*^L]$$

Source: Green and Mavor (1994, p. 127).

An explanation of the components that makeup the recruiting “cost minimization problem” is shown in Figure 5.

Figure 5. Recruiting Cost Minimization Component Roadmap

$$\overbrace{Min[\underbrace{p^R(R^H + R^M + R^L)}_{\text{Cost of Maintaining Recruiters}} + \underbrace{p^{AD}AD}_{\text{Cost of Advertising}} + \underbrace{C_*^H(B+E)}_{\text{Cost of Recruiting Incentives}} + \underbrace{T(C_*^H + C_*^M + C_*^L)}_{\text{Cost of Testing Recruits}} + \underbrace{O}_{\text{Fixed Costs}}]}^{\text{First Line: Recruiting Budget Formula}}$$

$$\underbrace{-\lambda_H[C^H + C_*^H] - \lambda_M[C^M - C_*^M] - \lambda_L[C^L - C_*^L]}_{\text{Second Line: Constraints to ensure desired recruiting mission is met}}$$

Adapted from Green and Mavor (1994, p. 127).

The first order conditions of the recruiting minimization problem are then "substituted" into the recruiting budget formula (i.e., the first line of the recruiting cost minimization problem shown in Figure 5) to "yield the recruiting cost function," shown in Figure 6 (Green & Mavor, 127).

Figure 6. Recruiting Cost Function

$$Minimum\ Cost\ Budget = \alpha Z(C_*^H)^{\frac{1+\alpha_B+\alpha_E}{\alpha}} + p^R\left[\left(\frac{C_*^M}{C_0^M}\right)^{\frac{1}{\alpha_R^M}} + \left(\frac{C_*^L}{C_0^L}\right)^{\frac{1}{\alpha_R^L}}\right]$$
$$+T(C_*^H + C_*^M + C_*^L) + O$$

$where:$

$$Z = \left[(C_0^H)^{\frac{-1}{\alpha}}(v)\frac{\alpha_B + \alpha_E}{\alpha}\left(\frac{\alpha_R^H}{p^R}\right)^{\frac{-\alpha_R^H}{\alpha}}\left(\frac{\alpha_{AD}}{p^{AD}}\right)^{\frac{-\alpha_{AD}}{\alpha}}(\alpha_B)^{\frac{-\alpha_B}{\alpha}}(\alpha_E)^{\frac{-\alpha_E}{\alpha}}(F)^{\frac{-\alpha_F}{\alpha}}\right]$$

$$and\ \alpha = \alpha_R^H + \alpha_{AD} + \alpha_B + \alpha_E$$

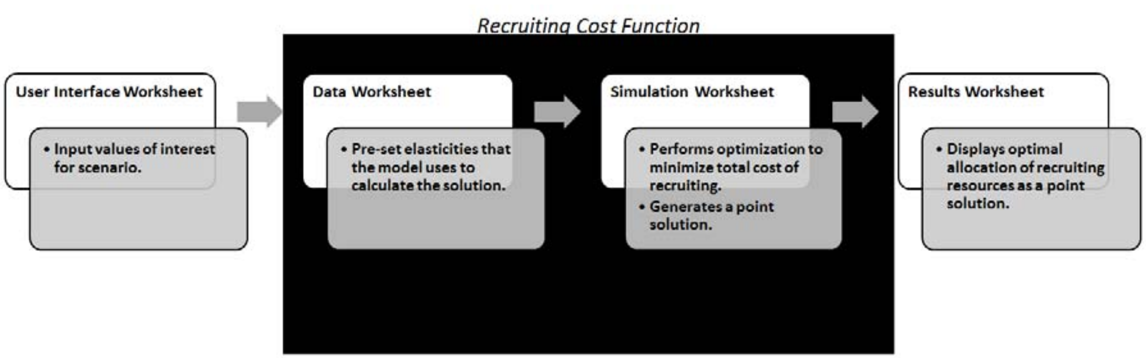
Adapted from Green and Mavor (1994, p. 127).

Elasticities within the recruiting cost function are parameters built into the model that “represent the percent change in enlistment contracts for a percent change in recruiting resources/incentives or market factors” (McCloy et al., 1992, p. 74). The PRO model elasticities were last revised when the SAG Corporation and The Lewin Group, Inc. updated the PRO model in September 2011 (Hogan, Warner, & Mackin, n.d.). More information about the derivation and specifics of the cost performance tradeoff model can be found in the “Job Performance, and Cost: A Cost-Performance Tradeoff Model” report and “Modeling Cost and Performance for Military Enlistment,” a report of a workshop (McCloy et al., 1992; Green & Mavor, 1994).

c. *Model Framework*

The PRO model is made up of four worksheets: (1) User Interface, (2) Inputs (will be referred to as the “Data Worksheet” in this research), (3) Simulation, and (4) Results. Figure 7 illustrates the conceptual flow and relationship between these worksheets.

Figure 7. Structure of the PRO Model



Adapted from Navy Recruiting Command (2007, p. 12).

The “User Interface” worksheet allows the user to enter values for each input variable, select which decision variables are fixed or to be optimized, and select how the model is run over seven FYs. The “Data Worksheet” and the “Simulation Worksheet” are components of the “black box” that makeup the

recruiting cost function. The “Results Worksheet” provides users with the optimal mix of recruiting resources to minimize the cost of recruiting. Each component of the PRO model is now explained in more detail.

2. PRO Model Variables

The variables of the PRO model are classified into three types: (1) decision variables, (2) market factors, and (3) policy factors. Variables are fed into the model through PRO’s “User Interface” Microsoft Excel worksheet, as shown in Figure 8.

Figure 8. The PRO Model User Interface

Step 1: Check input

Model Feeds:	FY15	FY16	FY17	FY18	FY19	FY20	FY21
NCF + College First	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Unemployment Rate	6.40%	5.10%	4.90%	4.80%	4.80%	4.80%	4.80%
Recruiters	3,913	3,685	3,685	3,685	3,685	3,685	3,685
LRP	7.440	11.220	11.280	11.380	11.430	11.460	11.670
Advertising (AC Enl. Only)	34.826	34.699	35.679	36.729	39.886	38.892	39.669
EB	40.971	36.580	41.340	40.650	42.230	42.060	42.810
NCO (50% BoY DEP)	35,025	36,425	36,800	35,800	35,225	34,650	34,650

Step 2: Select switches

	Total Recruiters	Float
Fixed	Advertising	Float
Float	Bonus	Fixed
	Education	Float

Step 3: Select Best/Worst Cases for Unemployment

POR +/- Range — Range (+/-) 0.50%

	High UE Case	7.40%	6.10%	5.90%	5.80%	5.80%	5.80%	5.80%
POR +/- Range	Base UE Case	6.90%	5.60%	5.40%	5.30%	5.30%	5.30%	5.30%
Manual Forecast	Low UE Case	6.40%	5.10%	4.90%	4.80%	4.80%	4.80%	4.80%
	Manual Forecast							
	High UE	5.00%	5.00%	5.00%	5.00%	5.00%	5.00%	5.00%
	Consensus UE	4.50%	4.50%	4.50%	4.50%	4.50%	4.50%	4.50%
	Low UE	4.00%	4.00%	4.00%	4.00%	4.00%	4.00%	4.00%

Step 4: Select run type

Traditional Run — Capacity Run

POM FY17 version of the PRO model.

a. *Decision Variables*

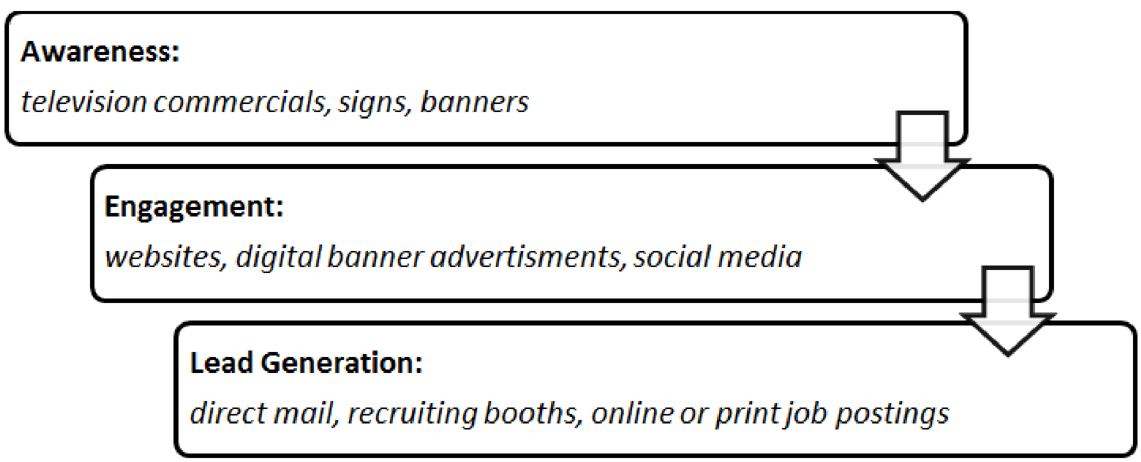
The decision variables of the PRO model are the resources that the Navy controls. N1 can influence how much is budgeted toward advertising, how many production recruiters are in the field, and how funding is allocated for enlistment

bonuses and education incentives. It is useful to know the optimal balance between these resources, since once money is allocated to a certain resource, those funds cannot be used for anything else. For example, funds appropriated for recruiters cannot be used to fund advertising (Morey & McCann, 1980, p. 1198).

(1) Advertising

Advertising is defined by the United States Government Accountability Office (GAO) as "the placement of messages intended to inform or persuade an audience through various types of media such as television, radio, digital media, direct mail, and others" (GAO, 2016, p. 1). Each military service, including the Navy, uses the advertising construct shown in Figure 9 to "raise the public's awareness… and help recruiters generate leads of potential recruits" (GAO, 2016, p. 1). A lead is someone who shows interest in joining the Navy. Leads can be generated a variety of ways, from face-to-face interactions with a recruiter to indirect contact through advertisement efforts.

Figure 9. Phases and Goals of Military Advertisement



Adapted from GAO (2016, p. 7).

Military advertising efforts are in line with the "consumer journey" construct found in the private sector. The goal is "to move a potential recruit through each phase and, ultimately, to a decision to enlist" (GAO, 2016, p. 7). The Navy

typically allocates about $50 million each FY towards advertising. Table 1 shows a breakdown of how much the Navy has annually allotted for advertising over the past three FYs in comparison to the other military services (GAO, 2016, p. 41).

Table 1. Reported Annual Allotments for Military Advertising

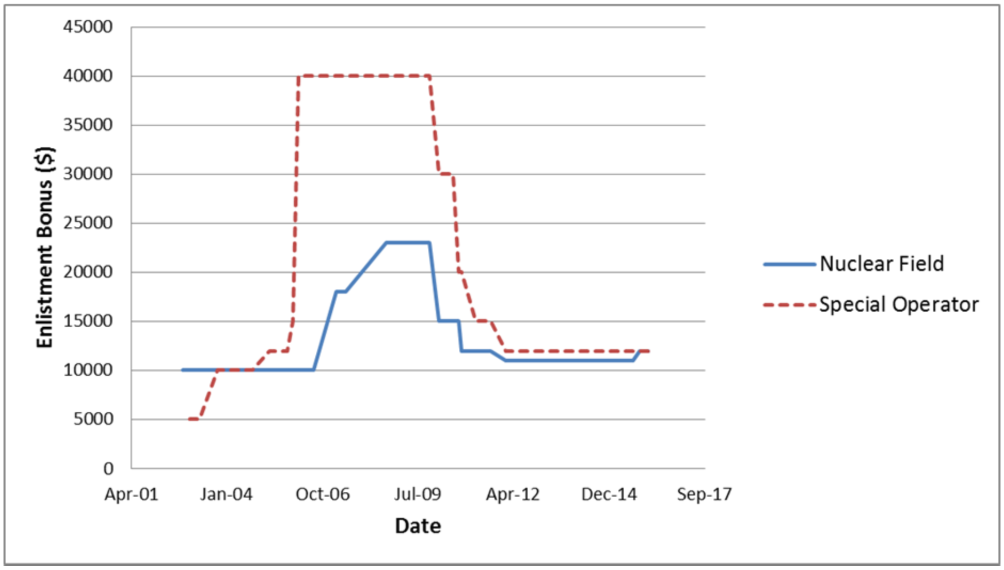
	2015 Actuals	**2016 Enacted**	**2017 Estimate**
Navy	$56,100,000	$49,000,000	$47,000,000
Army	$367,700,000	$238,100,000	$292,600,000
Air Force	$59,400,000	$35,900,000	$60,300,000
Marine Corps	$86,300,000	$81,500,000	$81,800,000

These values include active duty and reserve recruiting budgets. Adapted from GAO (2016, p. 41).

(2) Enlistment Bonus

Enlistment bonuses are used to incentivize high quality applicants to join the Navy. Enlistment bonuses are tied to specific Navy occupational specialties. Special warfare (Navy sea, air, and land (SEAL) operators) and nuclear field (NF) specialties are examples of Navy occupational specialties that require high ASVAB scores, and regularly offer an enlistment bonus to recruits. Figure 10 shows the individual enlistment bonus offered to each recruit who enlisted as a special operator or in the nuclear field. Enlistment bonuses fluctuate for many reasons, to include: the time of year the recruit ships to boot camp, and under or over manning strength of the Navy occupational specialty (Navy Recruiting Command, n.d.).

Figure 10. Enlistment Bonus Offered to NF and Special Operator Recruits



Data gathered from Navy Recruiting Command enlistment bonus messages from October 2002 to February 2016. Adapted from Navy Recruiting Command (n.d.).

(3) Production Recruiters

Production recruiters are Navy Sailors assigned to recruiting duty with the 9585 Navy Enlisted Classification (NEC) code. For model simplicity, the PRO model divides production recruiters into three quality categories: low, medium, and high. The model designates high quality recruiters to recruit only high quality applicants, and so on. Navy Recruiting Command (NRC) does not separate recruiters into these tiered categories. This simplifying assumption helps represent that “high-quality personnel cost more to recruit” (Green & Mavor, 1994, p. 10–11).

The number of production recruiters in the field directly affects the total cost of recruiting. The PRO model takes recruiter’s base pay and individual support costs into consideration when calculating the cost of recruiting.

(4) Education Incentive

Following the enactment of the Post 9/11 GI Bill in June of 2008, the Navy has not allocated funds towards the legacy Navy college fund (NCF) for new

recruits (Dortch, 2014, p. 1; Palmer, personal communication, June 2016). The Post 9/11 GI Bill provides service members who have served on active duty following September 10, 2001, with education benefits that "can cover all in-state tuition and fees at public degree granting schools" along with support programs for out-of-state and private institutions (Department of Veterans Affairs, 2012).

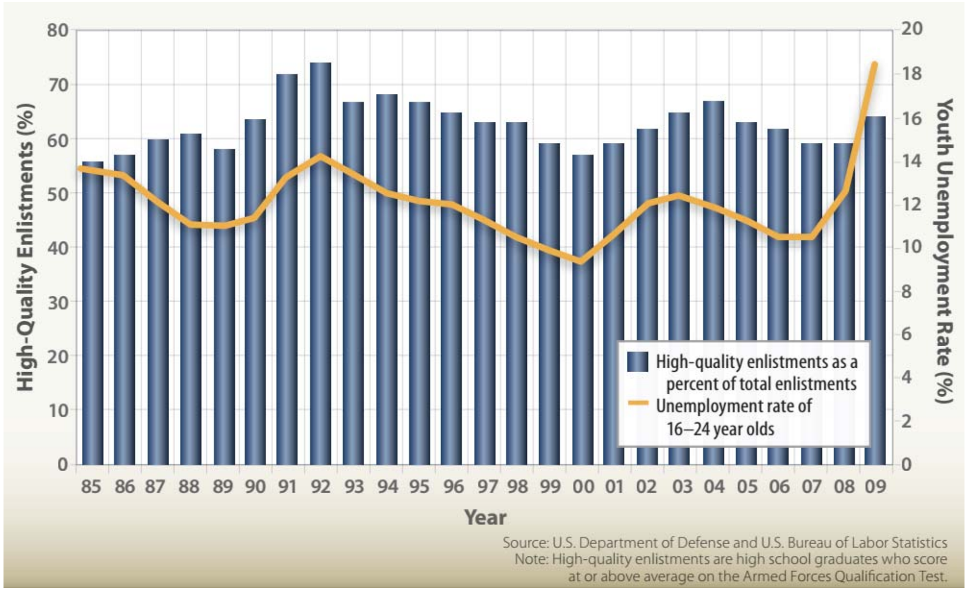
b. Market Factors of the PRO Model

Market factors of the PRO model are economically and demographically driven variables that are uncontrollable and subject to unexpected change.

(1) Unemployment Rate

Unemployment rates are shown to be "positively and significantly related to high-quality enlistment contracts" (Asch et al., 2010, p. 21). As shown in Figure 8, this trend indicates that higher unemployment rates lead to more high quality enlistment contracts (Bicksler & Nolan, 2009, p. 5). Figure 11 shows data aggregated for all military services.

Figure 11. Unemployment and High-quality Enlistments



Source: Bicksler and Nolan (2009, p. 5).

(2) Relative Pay

Like unemployment rates, military recruiting for high quality applicants responds “to the level of military pay relative to civilian sector wage opportunities” (Warner, 2012, p. 71). The PRO model captures this market driver through the relative pay ratio. Since the Navy requires high quality Sailors who are technically competent, “pay comparability… is an issue for certain hard-to-fill occupations and skills that command high salaries in the civilian sector, particularly in high technology fields” (Bicksler & Nolan, 2009, p. 34). Table 2 provides interpretations of relative pay ratios.

Table 2. Interpretations of Relative Pay

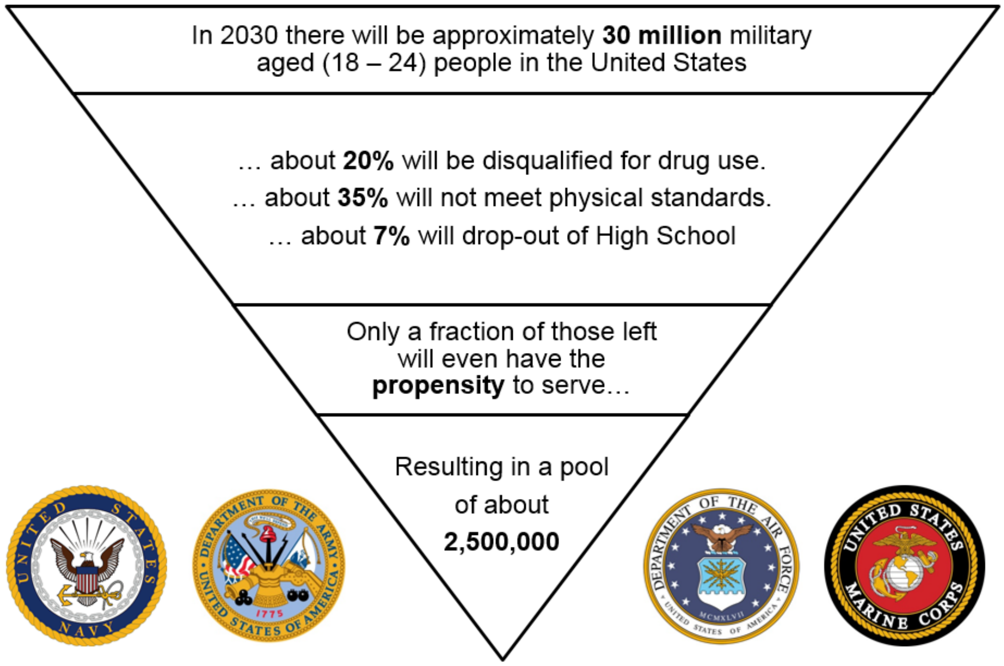
Relative Pay	Interpretation
0.5	Military pay is 50 cents to every dollar of civilian sector pay.
1.0	Military pay is equal to civilian sector pay.
2.0	Civilian sector pay is 50 cents to every dollar of military pay.

(3) Qualified Military Available

Qualified military available (QMA) is an estimate of the “17- to 24-year-old youth population in the United States who would qualify without needing a waiver and be available to enlist in the active component military” (Office of the Undersecretary of Defense, 2016, p. 2). An independent firm, Woods and Poole Economics, provides the Navy with QMA data (www.woodsandpoole.com).

Some common disqualifiers for applicants joining the military include: illicit drug use, overweight/obesity, use of prescribed psychotropic drugs, and failure to complete high school. Figure 12 is a hypothetical model which depicts the QMA pool for the recruiting efforts of the four military services. The resulting pool of QMA is just a small portion of the overall military-aged population within the United States.

Figure 12. Hypothetical Breakdown for Estimated QMA Pool in 2030



Data approximations are adapted from MarketingCharts (2016); Child Trends Data Bank (2014); Child Trends Data Bank (2016); National Center for Education Statistics (2016). Propensity to serve metric is omitted due to distribution restrictions.

Other factors that are not considered include the percentage of young adults who are currently enrolled in college, those who are permanently employed, or those who may have dependents.

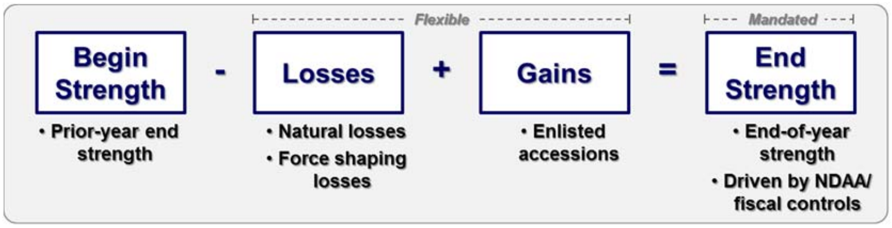
c. Policy Factors of the PRO Model

Policy factors are variables that can be adjusted, but are done through a combination of policy, service culture, and budget changes.

(1) New Contract Objective

The new contract objective (NCO) is the Navy's enlisted accession mission for a given FY. NRC's NCO goal each FY is dependent on the Navy's projected end-strength. The equation for end-strength is shown in Figure 13.

Figure 13. Equation for Navy Enlisted Strength Planning



Adapted from Dave Clark's 2015 presentation at the Naval Postgraduate School (personal communication, (September 10, 2015).

Force planners at N1 forecast the number of Sailors who will leave the Navy each year; referred to as manning losses. NRC's NCO goal ensures that the Navy's force strength meets the congressionally mandated end-strength for each FY (Clark, personal communication, 2015). Table 3 demonstrates the different phases of Navy manning within a FY. The NCO mission is dynamic and often fluctuates throughout the FY in response to actual manning losses.

Table 3. Navy Manning Terminology

Terminology	Description
Begin Strength	Current onboard as of October 1 of current FY
Force Strength	Current onboard anytime between October 2 and September 29 of current FY.
End Strength	Current onboard as of September 30 of current FY

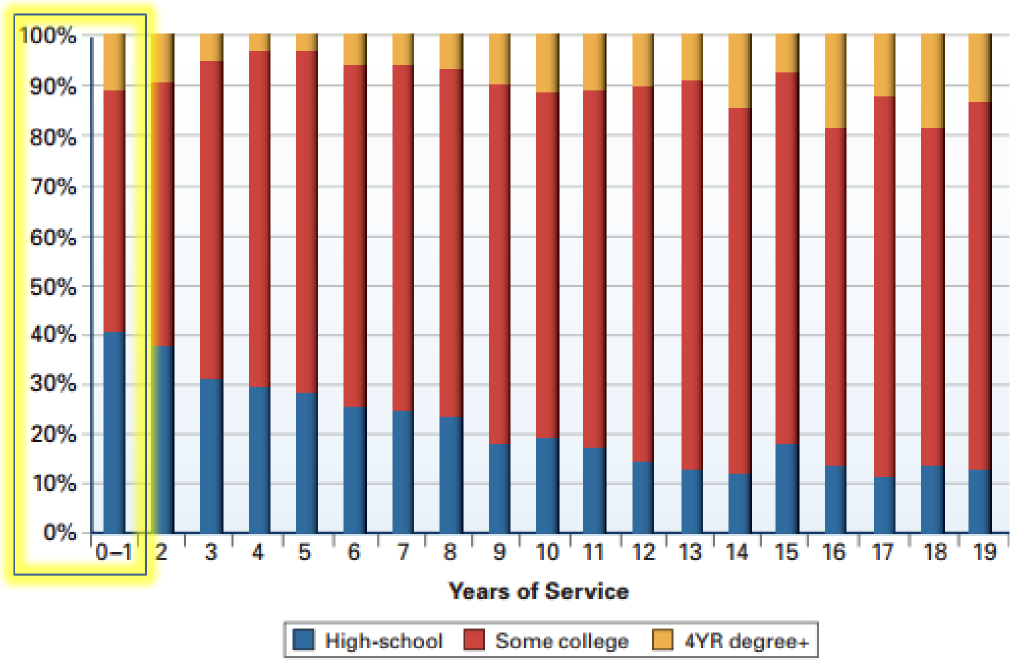
The first day of the FY is October 1 and the last day of the FY is September 30.

(2) Loan Repayment Program

The loan repayment program (LRP) is an incentive that the Navy uses to attract high quality applicants with student loan debt to enlist in specific occupational specialties. Assuming enlisted service members with less than one year of service pursued higher education prior to joining the military, Figure 14 indicates that approximately 60 percent of recruits across all military branches have attended at least some college before joining the military. Figure 14

includes credits towards an undergraduate degree, a completed undergraduate degree, and postgraduate education.

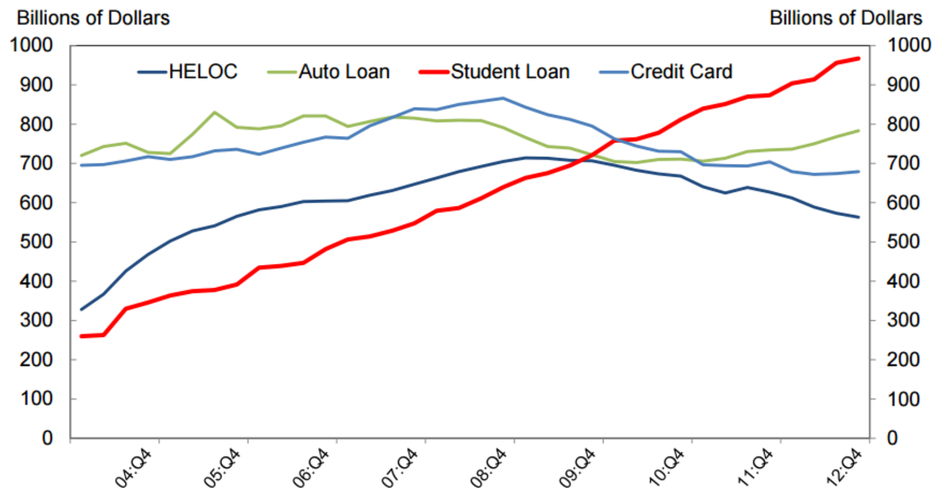
Figure 14. Education Levels of Enlisted Personnel



Assuming that service members who have between 0–1 year of service enlisted into the service with the education level shown. Source: Grefer, Gregory, and Rebhan (2011, p. 10).

Through the LRP, the Navy "pay[s] federally guaranteed student loans (up to $65,000) through three annual payments during a Sailor's first three years of service" (Navy Recruiting Command, 2017). Student loan debt "is the only form of consumer debt that has grown since the peak of consumer debt in 2008," as shown in Figure 15 (Lee, 2013, p. 5).

Figure 15. Rise of Student Debt



Source: Lee (2013, p. 5).

Consequently, the military's loan repayment program may be an attractive option for a high quality recruit with student loan debt.

(3) High School Diploma

Studies indicate that a high school diploma is "a valuable predictor of military attrition" (Buddin, 1984, p. 2). Recruits who do not have a high school diploma are more likely to not finish their initial obligated military service. In response to this "well-known result," the DOD has a benchmark that at least 90 percent of new accessions must join the military with a high school diploma (Navy Recruiting Command, 2007, p. 7; Buddin, 1984, p. 1). A general education development (GED) certificate is not considered a high school diploma (Buddin, 1984, p. 1).

(4) Recruit Quality

Recruit quality is determined by an applicant's Armed Forces Qualification Test (AFQT) score. The AFQT score is derived from the ASVAB's "Arithmetic Reasoning (AR), Mathematics Knowledge (MK), Paragraph Comprehension (PC), and Word Knowledge (WK)" subsections (Defense Management Data Center, n.d.).

High school graduates who earn above a 50 AFQT are classified as “high quality” applicants (Navy Recruiting Command, 2007, p. 6). The term high quality is also referred to as Test Score Category (TSC) I-IIIA. This group is represented by the “A” block in Figure 16.

Figure 16. Navy Recruit Quality Determination

AFQT	TSC	High School Diploma	No High School Diploma
99 - 93	I	A	B
93 - 65	II		
65 - 50	IIIA		
50 - 31	IIIB	Cu	D
31 - 0	IVa	Cl	
	IVb		
	IVc		
	V	DOD Ineligible	

Adapted from Navy Recruiting Command (2007, p. 7).

The Navy aims to recruit applicants who meet the group “A” requirement because they qualify for most Navy occupational specialties, have the lowest first term attrition rate, historically encounter fewer disciplinary problems, and are likely to have the best career performance. However, this category of applicants tends to be the most expensive to recruit (Navy Recruiting Command, 2007, p. 7).

High quality applicants typically have multiple opportunities, such as college or a well-paying job. Therefore, the Navy must invest more money in advertisements targeting group “A,” increase enlistment bonuses to incentivize group “A,” and increase recruiting manpower to recruit group “A” applicants. Each of these contribute to the high cost of recruiting high quality applicants.

Descriptions and characteristics of all categories represented in Figure 16 are explained in Table 4.

Table 4. Recruit Quality Category Description

Block/Category	Description
A	(1) Qualify for the most amount of programs (2) Have the lowest first term attrition (3) Encounter fewer disciplinary problems (4) Likely to have the best career performance
B	(1) Highest first term attrition rate (2) Qualify for many programs
Cu	(1) Attrition lower than “B,” but higher than “A” (2) Applicants do not qualify for many programs.
Cl	Navy does not recruit from this group
D	Navy does not recruit from this group

Adapted from Navy Recruiting Command (2007, p. 7).

d. PRO Model: Run Options

PRO model excursions can be run two different ways; (1) traditional run, or (2) capacity run.

(1) Traditional Run

The traditional run option of the PRO model performs an optimization that minimizes the cost of recruiting by determining the optimal allocation of resource spending to advertisements, enlistment bonuses, education incentives, and recruiters. The traditional run can be evaluated as either an unconstrained or a constrained problem.

An unconstrained traditional run does not bound any of the decision variables. The result is “an unconstrained, minimum cost solution” (Navy Recruiting Command, 2007, p. 22). Unconstrained traditional runs may produce results that are mathematically feasible, but are infeasible in practice. For example, while it would be unrealistic for NRC to have more than 4,000 recruiters in the field, the PRO model may determine 4,520 recruiters to be the optimal solution.

Figure 17 shows the results of an unconstrained traditional run of the PRO model. The highlighted rows are the results. In FY 2015, with a 5 percent unemployment rate, and a recruiting mission of 34,000, the optimal allocation of

recruiting resources to minimize the cost of recruiting was: assign 3,137 Sailors to recruiting duty, allocate $50,960,000 to advertising, and $67,267,000 to enlistment bonuses.

Figure 17. Results of an Unconstrained PRO Model Run

	Resource Run	2015	2016	2017	2018	2019	2020	2021
	NCO	34,000	34,000	34,000	34,000	34,000	34,000	34,325
	Capacity	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Unemployment (%)	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Float	Total Recruiters	3,137	3,132	3,125	3,117	3,110	3,101	3,141
	Total Recruiter Cost ($M)	$256.944	$259.364	$262.626	$265.932	$269.281	$273.186	$281.505
Float	Advertising ($M)	$50.960	$51.329	$51.798	$52.272	$52.750	$53.293	$55.170
Float	Enlistment Bonus ($M)	$67.267	$67.754	$68.374	$68.999	$69.630	$70.346	$72.825
Float	Education Incentives ($M)	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000
	LRP ($M)	$7.440	$11.220	$11.280	$11.380	$11.430	$11.460	$11.670
	HSDG	95%	95%	95%	95%	95%	95%	95%
	TSC I-IIIA	70%	70%	70%	70%	70%	70%	70%
	Total Cost ($M)	$382.611	$389.667	$394.078	$398.583	$403.091	$408.285	$421.170

POM FY17 version of the PRO model.

In contrast, a constrained traditional run fixes at least one of the four decision variables. The decision variables that are fixed remain constant. The remaining unconstrained decision variables are optimized (Navy Recruiting Command, 2007, p. 22).

Figure 18 demonstrates the results of a constrained traditional PRO model run where advertising and enlistment bonus were fixed and the total number of recruiters was optimized.

Figure 18. Results of a Constrained Traditional PRO Model Run

	Resource Run	2015	2016	2017	2018	2019	2020	2021
	NCO	34,000	34,000	34,000	34,000	34,000	34,000	34,325
	Capacity	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Unemployment (%)	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Float	Total Recruiters	3,037	3,042	3,047	3,052	3,058	3,063	3,151
	Total Recruiter Cost ($M)	$248.724	$251.880	$256.097	$260.386	$264.747	$269.825	$282.408
Fixed	Advertising ($M)	$60.000	$60.000	$60.000	$60.000	$60.000	$60.000	$60.000
Fixed	Enlistment Bonus ($M)	$67.500	$67.500	$67.500	$67.500	$67.500	$67.500	$67.500
Float	Education Incentives ($M)	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000
	LRP ($M)	$7.440	$11.220	$11.280	$11.380	$11.430	$11.460	$11.670
	HSDG	95%	95%	95%	95%	95%	95%	95%
	TSC I-IIIA	70%	70%	70%	70%	70%	70%	70%
	Total Cost ($M)	$383.664	$390.600	$394.877	$399.266	$403.677	$408.785	$421.578

POM FY17 version of the PRO model.

The highlighted rows are the results. In FY 2015, with a 5 percent unemployment rate, a recruiting mission of 34,000, advertising fixed at $60,000,000, and enlistment bonuses fixed at $67,500,000, the Navy should assign 3,037 Sailors to recruiting duty.

(2) Capacity Run

The capacity run estimates the number of recruits the Navy can expect to recruit based on a predetermined allocation of recruiting resources. Figure 19 exhibits the results of a capacity run.

Figure 19. Results of a Capacity PRO Model Run

Capacity Run	2015	2016	2017	2018	2019	2020	2021
NCO	34,000	34,000	34,000	34,000	34,000	34,000	34,325
Capacity	33,426	33,405	33,385	33,364	33,344	33,324	33,303
Unemployment (%)	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Total Recruiters	2,900	2,900	2,900	2,900	2,900	2,900	2,900
Total Recruiter Cost ($M)	$237.520	$240.119	$243.725	$247.381	$251.093	$255.477	$259.917
Advertising ($M)	$60.000	$60.000	$60.000	$60.000	$60.000	$60.000	$60.000
Enlistment Bonus ($M)	$67.500	$67.500	$67.500	$67.500	$67.500	$67.500	$67.500
Education Incentives ($M)	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000
LRP ($M)	$7.440	$7.440	$11.220	$11.280	$11.380	$11.430	$11.460
HSDG	95%	95%	95%	95%	95%	95%	95%
TSC I-IIIA	70%	70%	70%	70%	70%	70%	70%
Total Cost ($M)	$372.460	$375.059	$382.445	$386.161	$389.974	$394.407	$398.877

POM FY17 version of the PRO model.

The results indicate that in FY 2015 the Navy can expect 33,426 recruits with 2,900 recruiters in the field, $60,000,000 allocated to advertising, and $67,500,000 allocated to enlistment bonuses.

3. Updates to the PRO Model

In 2011 the SAG Corporation and The Lewin Group, Inc. updated the PRO model based on specific shortcomings of the model identified by the Navy (Hogan et al., n.d., p. 1). The updated model is referred to as the Recruiting Program Resource Optimization (E-PRO) model. The E-PRO model added “stochastic forecasting capability” and updated the econometric elasticities within the recruiting cost function (Hogan et al., n.d., p. 3).

Despite these updates, analysts at N1 still use the PRO model since it is "simpler in construct [compared to E-PRO]… and delivers very good results" (Palmer, personal communication, April 7, 2016). As mentioned earlier, the current version of the PRO model uses "the pooled baseline elasticities updated from the… [2011] E-Pro effort" (Palmer, personal communication, April 12, 2016).

4. Limitations of the PRO Model

The existing PRO model does not have the capability to efficiently test uncertainties in variable values, or the effects of variable interactions. Without this capability, PRO model users must use either manual trial and error techniques to test different scenarios individually, or build macros in Excel to test the fluctuation of a single variable. For example, a macro was written to test three levels of unemployment rate, as shown in Table 5.

Table 5. Pooled Unemployment Rates

	FY 15	FY16	FY17	FY18	FY19	FY 20	FY21
High UE	5.00%	5.00%	5.00%	5.00%	5.00%	5.00%	5.00%
Base UE	4.50%	4.50%	4.50%	4.50%	4.50%	4.50%	4.50%
Low UE	4.00%	4.00%	4.00%	4.00%	4.00%	4.00%	4.00%

Adapted from POM FY17 version of the PRO model.

Without options for multivariable sensitivity analysis or efficient experimentation, it is difficult to understand how variable interactions or fluctuations in controllable and uncontrollable factors affect the model's output. This may be an area of concern when the output is used to help inform decisions involving hundreds of millions of dollars.

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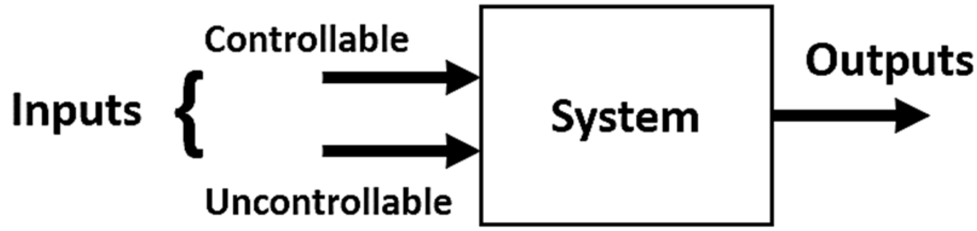
III. METHODOLOGY AND IMPLEMENTATION

This chapter covers three main topics that span the motivation, design, and implementation of PROM-WED. First, an overview of design of experiments techniques is presented. Next, the field of data farming is introduced to include examples of past research studies that have utilized data farming. Finally, these two concepts are integrated as the design and construction of PROM-WED is explained.

A. DESIGN OF EXPERIMENTS

The objective of an experiment across any discipline of study is “to investigate characteristics of a system” (Park, 2007, p. 309). There are no limits to what this system can be, from the test and evaluation of a new military warship, to sensitivity analysis on a political science poll. Every system has inputs and outputs. Inputs are either controllable or uncontrollable. Controllable factors are input variables to the system that are known and can be set, such as the number of Navy destroyers that enter a theater of operations in a combat simulation, to the number of production recruiters Navy Recruiting Command has in the continental United States. Uncontrollable factors are input variables to the system that are uncertain, such as the unemployment rate in 2021, or the probability of kill for an adversary’s new weapon system. A general model of a system is shown in Figure 20.

Figure 20. General Model of a System.



Adapted from Penn State (n.d.).

Early development in DOE methodology occurred predominately in the physical sciences, specifically in agriculture (Penn State, n.d.). The classical methods and foundations of DOE can also be applied to the testing and analysis of simulation models (Sanchez, 2006, p. 69). Control, replication, and randomization are considered to be "fundamental concepts" of DOE (Sanchez, 2006, p. 69). Working definitions of these concepts in the context of DOE are shown in Table 6.

Table 6. Fundamental Concepts of DOE.

Fundamental Concept	Working Definition
Control	"The experiment is conducted in a systematic manner after explicitly considering potential sources of error, ***rather than by using a trial-and-error* approach.***"
Replication	"A way to gain enough data to achieve narrow confidence intervals and powerful hypothesis tests."
Randomization	"Provides a probabilistic guard against the possibility of unknown, hidden sources of bias surfacing to create problems with your data."

Adapted from Sanchez (2006, 69).

To adequately test a system, whether the system is a simulation model or a physical science experiment, trial-and-error should be avoided. Trial-and-error is inefficient, difficult to replicate, and lacks control. DOE techniques combat these limitations through systematically testing a model with control, replication, and randomization. Systematic approaches are also conducive for automation, which alleviates manual work, and increases the efficiency and capability of the system being explored. The automation of DOE techniques has created the field of data farming, which is further explained in the next section.

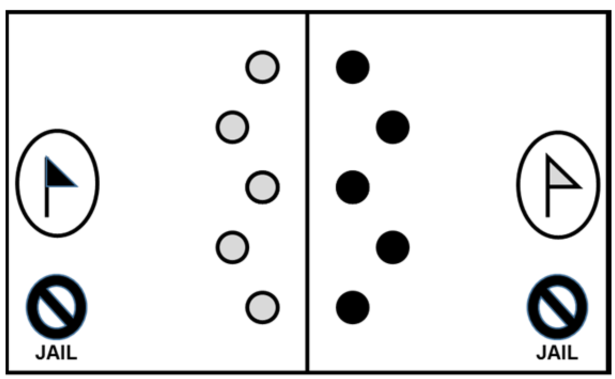
There are many different DOE methods and techniques available, such as the full and fractional factorials, central composite designs, and nearly orthogonal Latin hypercubes (NOLHs). The full factorial and NOLH methods are explained in further detail. More information regarding DOE basic concepts, methods and

their application to simulation modeling can be found in Sanchez and Wan's report, "Work Smarter, Not Harder: A tutorial on designing and conducting simulation experiments" (Sanchez & Wan, 2015).

1. Full Factorial DOE Method

The full factorial approach tests every possible combination of input factors given fixed levels. The classic game of "capture the flag" is used to explain the full factorial method. The objective of the game is for a member of one team to capture a flag that is kept on the other side of the field, and return it to their side of the field. If caught by a member of the opposing team on the opposition's side of the field, the player fails the mission, and is temporarily placed in "jail." Figure 21 shows a simple representation of the "capture the flag" game, where the gray team on the left is trying to capture the gray flag on the opposition's side, and vice versa.

Figure 21. Capture the Flag Game

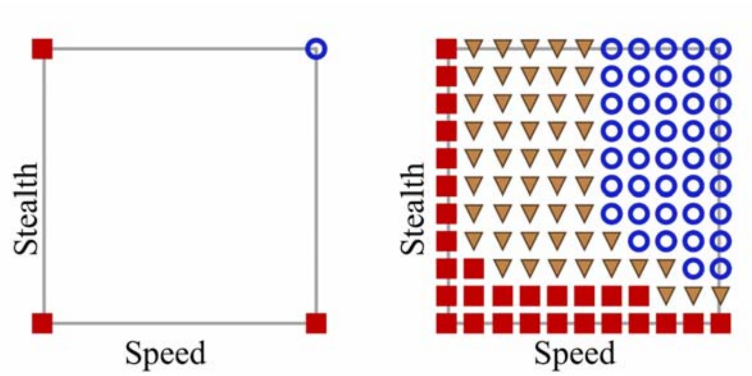


The circles represent the players of each team. Adapted from MultiCulturalGames (n.d.).

Two attributes that may affect the success of a "capture the flag" player are speed and stealth. Figure 22 illustrates the testing of various degrees of speed and stealth for a "capture the flag" player. The sparse grid on the left tests the system only at its extreme values, where either minimum speed or minimum stealth results in a failure, but maximum speed and maximum stealth results in a

success. The grid on the right demonstrates a dense full factorial test where many possible levels of stealth are tested against many possible levels of speed. In this hypothetical example, success can be met at something other than a combination of full speed and full stealth (Sanchez & Wan, 2015, p. 1801).

Figure 22. A Sparse versus a Dense Full Factorial DOE for Capture the Flag



The block shapes indicate failure, whereas the circle indicates success. The triangle represents a result somewhere in between failure and success. Source: Sanchez and Wan (2015, p. 1801).

The dense full factorial grid in Figure 22 illustrates two key advantages that DOE techniques can offer: (1) space-filling capability, and (2) robust insight and understanding of the solution space.

Space-filling refers to a DOE's capability of testing the simulation over a broad spectrum of input combinations (Sanchez & Wan, 2015). Figure 22 demonstrates that testing only the maximum and minimum values does not have good space-filling capability, whereas using the multi-level full factorial DOE exemplifies high space-filling capability. The ability to test a factor at different levels increases the potential insight gained from the solution space (Sanchez & Wan, 2015). As demonstrated in Figure 22, the space-filling DOE provides insight to capture the flag players that the right combination of stealth and speed resources can achieve the target solution using less resources. Full factorial DOEs are orthogonal, which means that there are no confounding effects.

Certain combinations of input variables, such as speed and stealth, may influence the effect of each other. This is referred to as a variable interaction. Variable interactions identify "whether the levels of some factors influence the effects that other factors have" on the solution (Sanchez & Wan, 2015, p. 1796). Without proper care in designing experiments, interactions can be impossible to estimate.

Time and computing capability can quickly become limiting factors when performing DOE tests on complex simulation models. Testing a complex model using a full factorial of all possible combinations of variables is inefficient and often inconceivable. For example, Table 7 demonstrates how a DOE that examines a model with only 20 factors can quickly become infeasible as the number of levels increases.

Table 7. Number of Experiments Required to Test a Model with 20 Factors Using Full Factorial Designs

Number of levels each factor is studied at	Equation	Number of Experiments Required
2 *(i.e., only a min and max value)*	2^{20}	1,048,576
4 *(i.e., min, max and 2 values in between)*	4^{20}	1,099,510,000,000
6 *(i.e., min, max and 4 values in between)*	6^{20}	365,616,000,000,000

Adapted from Sanchez (2006, p. 76).

Increasing the number of experiments becomes costly since more experimental runs require higher computing capability, and increased work hours.

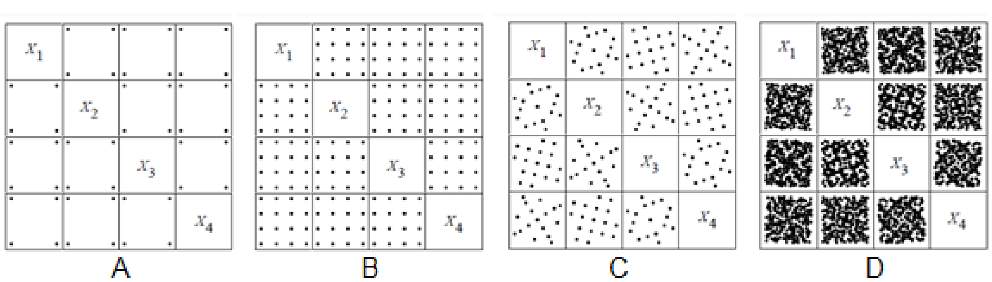
2. Nearly Orthogonal Latin Hypercubes

Cioppa and Lucas (2007) developed the nearly orthogonal Latin hypercubes (NOLH) which are efficient and effective alternatives to the full factorial DOE. “Latin hypercube designs have proven useful for exploring complex, high-dimensional computational models, but can be plagued with unacceptable correlations among input variables” (Hernandez, Lucas, & Carlyle, 2012, p. 1). Cioppa and Lucas’ work addresses this problem by “inducing small correlations between the columns in the design matrix” (2007, p. 45). The result is the nearly orthogonal Latin hypercube. These NOLH DOEs provide analysts with many advantages, including the ability:

> to determine the driving factors, detect interactions between input variables, identify points of diminishing or increasing rates of return, and find thresholds or change points in localized areas… [and] fit many diverse metamodels to multiple outputs with a single set of runs. (MacCalman, Vieira, & Lucas, 2016, p. 1)

Figure 23 shows a comparison of space-filling capabilities between two full factorial designs (A and B), versus two NOLH designs (C and D). The four designs are respectively a 2^4 and a 4^4 full factorial designs, and a 17-point and 257-point NOLH DOEs.

Figure 23. Pairwise Plot Matrices of DOE Designs



Source: Sanchez and Wan (2015, p. 1802).

Table 8 provides a numerical representation of the four DOE designs shown in Figure 23. For one extra design point (i.e., 16 to 17, or 256 to 257), we get much greater space filling with the NOLH DOE.

Table 8. Factorial Designs versus NOLH Designs

Pairwise Plot Matrix	Design	Factors	Levels	Design Points
A	2^4 Factorial	4	2	16
B	4^4 Factorial	4	4	256
C	NOLH	7	17	17
D	NOLH	29	257	257

Adapted from Sanchez and Wan (2015, p. 1802).

As demonstrated by Figure 23 and Table 8, the NOLH designs minimize computational effort while improving space-filling capability, allowing for more factors to be tested within the same experimental design (Sanchez & Wan, 2015, p. 1803). At the cost of one additional design point, we are able to analyze 7 or 29 factors at 17 and 257 levels, respectively, in comparison to a factorial design with 4 factors at either 2 or 4 levels. Reference Cioppa and Lucas' paper "Efficient Nearly Orthogonal and Space-filling Latin Hypercubes" for more information about the NOLH DOE method (Cioppa & Lucas, 2007).

From the initial research done by Cioppa and Lucas, other families of NOLH designs have been developed to enhance and make the NOLH designs adaptable to further applications in simulation analysis. To expand the NOLH designs capability a mixed integer program (MIP) algorithm was developed "that generates Latin hypercubes with little or no correlation among their columns for most any determinate run-variable combination" (Hernandez et al., 2012, p. 1). This MIP algorithm is also adaptable and accommodating to run modifications. (Hernandez et al., 2012, p. 1). A second-order NOLH design has also been developed that facilitates "exploratory analysis of stochastic simulation models in which there is considerable a priori uncertainty about the forms of the responses" (MacCalman et al., 2016, p. 1). Lastly, Sanchez created a Microsoft Excel spreadsheet that uses Cioppa and Lucas' NOLH DOE algorithm to provide users with the ability to generate designs ranging from simple small orthogonal Latin hypercubes to complex NOLH designs that handle up to 29 factors at 257 levels

each (Sanchez, 2011). These designs, along with other DOE methods, are available in Microsoft Excel format at https://harvest.nps.edu.

B. DATA FARMING

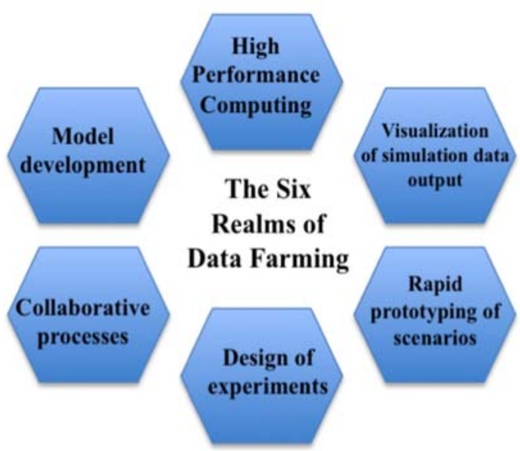
Work smarter, not harder…

—Professor Susan Sanchez (2006)

The use of robust design of experiment techniques has spawned a field of data analytics for simulation models, referred to as data farming. In comparison to traditional methods such as data mining, where one "seek[s] to uncover valuable nuggets of information buried within massive amounts of data," data farming grows data by controlling the interactions of the variables through efficient DOE techniques (Sanchez, 2014, p. 800). Retrospective data collection can find correlations, but prospective DOE is required to establish causality.

Data farming is an iterative process that allows analysts to gain robust insight into the "'big picture' solution landscape" (Horne & Meyer, 2010, p. 1). Six foundational components of data farming are shown in Figure 24.

Figure 24. The Six Realms of Data Farming



Source: Horne and Meyer (2010, p. 2).

Steve Upton of the SEED center at NPS has built multiple data farming wrappers to facilitate efficient DOE testing around simulation models spanning diverse computing environments and subject areas. The data farming wrappers that he builds are computer programs that wrap a DOE algorithm around a pre-existing model. The following is a sample of research that utilizes Upton's data farming wrappers:

1. Erin Borozny tested the Navy's Officer Strategic Analysis Model (OSAM) using data farming. OSAM is a manpower model that projects officer end strength and force structure based on "personnel plans and force-shaping policy" (Borozny, 2015, p. v). Her research provides insight into effective ways the Navy can better manage its officer inventory in order to meet authorized end strength at the end of each FY (Borozony, 2015).

2. Christian Seymour applied data farming to the Synthetic Theater Operations Research Model (STORM). The Department of Defense uses STORM as its "primary campaign analysis tool" that considers "force structures, operational concepts, and military capabilities" (Seymour, 2014, p. v). His study shows that data farming "capitalize[s] on STORM's full potential" and provides policy makers with robust insights in an efficient and effective manner (Seymour, 2014, p. v).

3. Jeffery Parker's research on the Marine Corps' future amphibious capability used data farming around a model that simulated amphibious assaults. His research provides informative decision support for United States Navy procurement "by evaluating the [Marine Expeditionary Unit's] MEU's expeditionary amphibious assault capability and the use of ship-to-shore connectors" (Parker, 2015, p. v).

These are only three examples of numerous studies that have utilized a data farming wrapper around a simulation model. They demonstrate how adaptable, capable, and valuable data farming an existing model can be. For more information about studies that have used data farming in defense applications, visit https://harvest.nps.edu.

C. PROM-WED

PROM-WED was developed to provide analysts with a tool that evaluates the PRO model over scenarios constructed using the NOLH DOE algorithm. PROM-WED also provides analysts with decision support capabilities that capitalize on its ability to grow data, and perform sensitivity and risk analysis to better inform decision makers on a robust solution to the optimal allocation of recruiting resources. PROM-WED excursions can be run to model the effects of varying degrees of policy changes and a range of economic and demographic conditions that affect the total cost of recruiting. One PROM-WED excursion provides decision support analysis to cover the effects of all of these factors and their interactions with one another.

To achieve these objectives, PROM-WED is divided into three main components: (1) the NOLH DOE data farming wrapper, (2) the GUI, and (3) decision support analysis. For the purpose of this research, focus is placed on the traditional run option. Refer to Chapter V regarding the capacity run option.

Since the PRO model is built in Microsoft Excel, PROM-WED is also built in Microsoft Excel, specifically Microsoft Excel 2013 Version 15.0.4849.1003 (Microsoft Excel, 2013). Given the restrictions and limitations of software allowed on government computers, maintaining PROM-WED in the Microsoft Excel environment allows accessibility of use to any government computer without requiring any additional software.

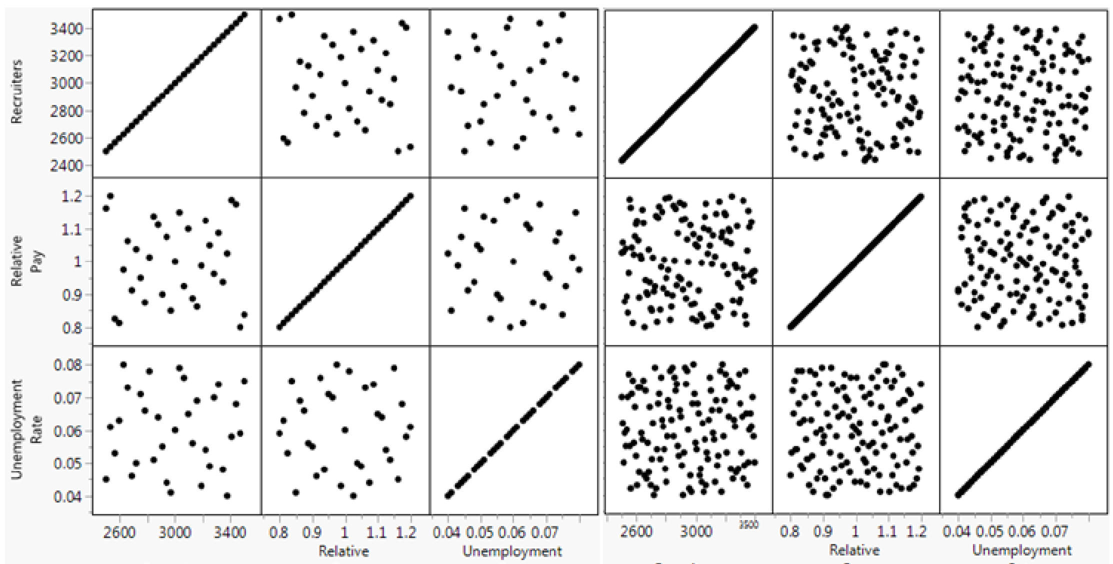
1. Data Farming Wrapper

The NOLH DOE algorithm is the foundation of PROM-WED's data farming wrapper. The NOLH was chosen for its space-filling capability and ease of use in a Microsoft Excel VBA modeling environment. The SEED Center at NPS has made the NOLH DOE algorithm available in a Microsoft Excel worksheet at https://harvest.nps.edu.

PROM-WED's data farming wrapper uses both the 33-point and 129-point NOLH design worksheets. The 33-point design tests up to 11 variables at 33

levels, whereas the 129-point design tests up to 22 variables over 129 levels. The 129-point design has better space-filling properties, but takes more time to run. Figure 25 shows a pairwise plot comparison of the space-filling ability of these two designs. The user is able to choose which NOLH design they want to run excursions over using the GUI that is further explained in the next section.

Figure 25. Pairwise Plots for the 33 and 129 Point NOLH Designs



Left: 33-point NOLH DOE. Right: 129-point NOLH DOE.

Table 9 shows an example PROM-WED test case scenario.

Table 9. Example PROM-WED Scenario

Variable Type	Variable Name	Value Low	Value High
Decision Variable	Production Recruiters	2,500 recruiters	3,500 recruiters
Market Factor	Unemployment Rate (UE)	4.0%	8.0%
Market Factor	Relative Pay	0.8	1.2
Policy Factor	Recruiting Mission (NCO)	30,000 recruits	40,000 recruits

Figure 26 shows the implementation of this scenario in the 33-point NOLH design worksheet. A 129-point NOLH design worksheet can be found in

Appendix A. Each FY that is explored has its own worksheet similar to the one seen in Figure 26 for FY 2017. PROM-WED provides users with a recruiting resource allocation over seven FYs. Therefore, there are seven 33-point NOLH design worksheets and seven 129-point NOLH design worksheets within PROM-WED's data farming wrapper.

Figure 26. Scenario Inputted into the NOLH Worksheet

	A	B	C	D	E	F	G	H	I	J	K	L
1	low level	0.0001	0.04	2500	11.28	34.8264	40.97	30000	0.7	0.95	0.8	1883304
2	high level	0.0001	0.08	3500	11.28	34.8264	40.97	40000	0.7	0.95	1.2	1883304
3	decimals	4	3	0	3	3	3	0	2	2	6	0
4	factor name	NCF + College First	Unemployment Rate	Recruiters	LRP	Advertising (AC Enl. Only)	EB	NCO (50% BoY DEP)	TSC I-IIIA	HSDG	ative Pay	QMA
5		0.0001	0.044	2938	11.28	34.826	40.97	36875	0.7	0.95	1.075	1883304
6	FY	0.0001	0.08	2625	11.28	34.826	40.97	37500	0.7	0.95	0.975	1883304
7	2017	0.0001	0.058	3406	11.28	34.826	40.97	37188	0.7	0.95	1.1875	1883304
8		0.0001	0.075	3500	11.28	34.826	40.97	38125	0.7	0.95	0.8375	1883304
9		0.0001	0.041	2969	11.28	34.826	40.97	34063	0.7	0.95	0.85	1883304
10		0.0001	0.078	2813	11.28	34.826	40.97	31563	0.7	0.95	1.0125	1883304
11		0.0001	0.059	3469	11.28	34.826	40.97	33750	0.7	0.95	0.8	1883304
12		0.0001	0.068	3438	11.28	34.826	40.97	32188	0.7	0.95	1.175	1883304
13		0.0001	0.05	2719	11.28	34.826	40.97	30000	0.7	0.95	1.0375	1883304
14		0.0001	0.066	2781	11.28	34.826	40.97	30938	0.7	0.95	0.875	1883304
15		0.0001	0.049	3250	11.28	34.826	40.97	31250	0.7	0.95	1.05	1883304
16		0.0001	0.069	3156	11.28	34.826	40.97	34688	0.7	0.95	0.8625	1883304
17		0.0001	0.046	2688	11.28	34.826	40.97	39688	0.7	0.95	0.9125	1883304
18		0.0001	0.064	2875	11.28	34.826	40.97	39375	0.7	0.95	1.1125	1883304
19		0.0001	0.048	3344	11.28	34.826	40.97	36563	0.7	0.95	0.9375	1883304
20		0.0001	0.065	3094	11.28	34.826	40.97	35625	0.7	0.95	1.1	1883304
21		0.0001	0.06	3000	11.28	34.826	40.97	35000	0.7	0.95	1	1883304
22		0.0001	0.076	3063	11.28	34.826	40.97	33125	0.7	0.95	0.925	1883304
23		0.0001	0.04	3375	11.28	34.826	40.97	32500	0.7	0.95	1.025	1883304
24		0.0001	0.063	2594	11.28	34.826	40.97	32813	0.7	0.95	0.8125	1883304
25		0.0001	0.045	2500	11.28	34.826	40.97	31875	0.7	0.95	1.1625	1883304
26		0.0001	0.079	3031	11.28	34.826	40.97	35938	0.7	0.95	1.15	1883304
27		0.0001	0.043	3188	11.28	34.826	40.97	38438	0.7	0.95	0.9875	1883304
28		0.0001	0.061	2531	11.28	34.826	40.97	36250	0.7	0.95	1.2	1883304
29		0.0001	0.053	2563	11.28	34.826	40.97	37813	0.7	0.95	0.825	1883304
30		0.0001	0.07	3281	11.28	34.826	40.97	40000	0.7	0.95	0.9625	1883304
31		0.0001	0.054	3219	11.28	34.826	40.97	39063	0.7	0.95	1.125	1883304
32		0.0001	0.071	2750	11.28	34.826	40.97	38750	0.7	0.95	0.95	1883304
33		0.0001	0.051	2844	11.28	34.826	40.97	35313	0.7	0.95	1.1375	1883304
34		0.0001	0.074	3313	11.28	34.826	40.97	30313	0.7	0.95	1.0875	1883304
35		0.0001	0.056	3125	11.28	34.826	40.97	30625	0.7	0.95	0.8875	1883304
36		0.0001	0.073	2656	11.28	34.826	40.97	33438	0.7	0.95	1.0625	1883304
37		0.0001	0.055	2906	11.28	34.826	40.97	34375	0.7	0.95	0.9	1883304

Figure 26 illustrates that each input, whether it be a controllable or uncontrollable variable, is tested over 33 levels. Recruiting mission, number of recruiters, UE, and relative pay are the variables that are tested over a range of values. The lower bound on the range is fed into the "low level" cell, whereas the upper bound on the range is fed into the "high level" cell. For the variables that remain constant, the low and high values are the same. The "decimals" cell refers to the number of significant digits in the decimal place that the NOLH algorithm divides the factor into. For example, recruiters, NCO, and QMA variables all have a zero in the "decimals" cell since these variables represent people, and having a fraction of a person is infeasible.

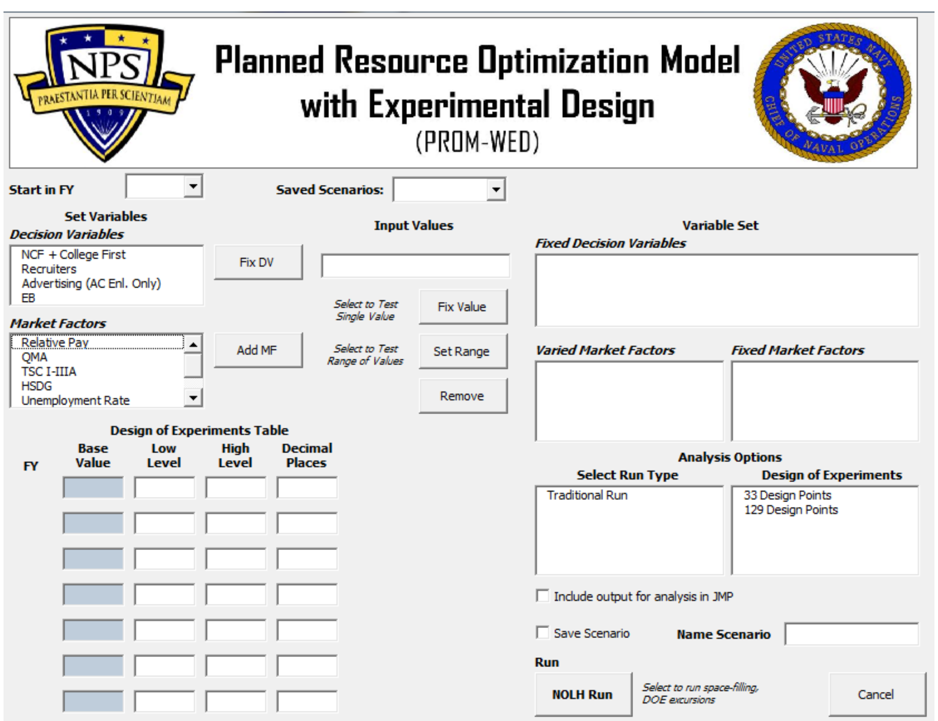
Each row of the worksheet shown in Figure 26 represents a different scenario. A subroutine loops over each row of the worksheet and feeds the values for each input variable into the legacy PRO model. The subroutine that executes 33 design point NOLH excursions can be found in Appendix B. The legacy PRO model's "RunTraditional" macro was adapted to accommodate data farming. The modified macro is now referred to as "RunTraditional6."

A 33-design point NOLH design will result in 33 different legacy PRO model solutions, and a 129-design point NOLH design will result in 129 different legacy PRO model solutions. The NOLH worksheet married with the subroutine makes up the data farming wrapper.

2. Graphical User Interface

PROM-WED's GUI makes data farming easily accessible to any PRO model user regardless of knowledge or skill in DOE techniques or data farming. A snapshot of PROMWED's GUI is shown in Figure 27.

Figure 27. PROM-WED's GUI

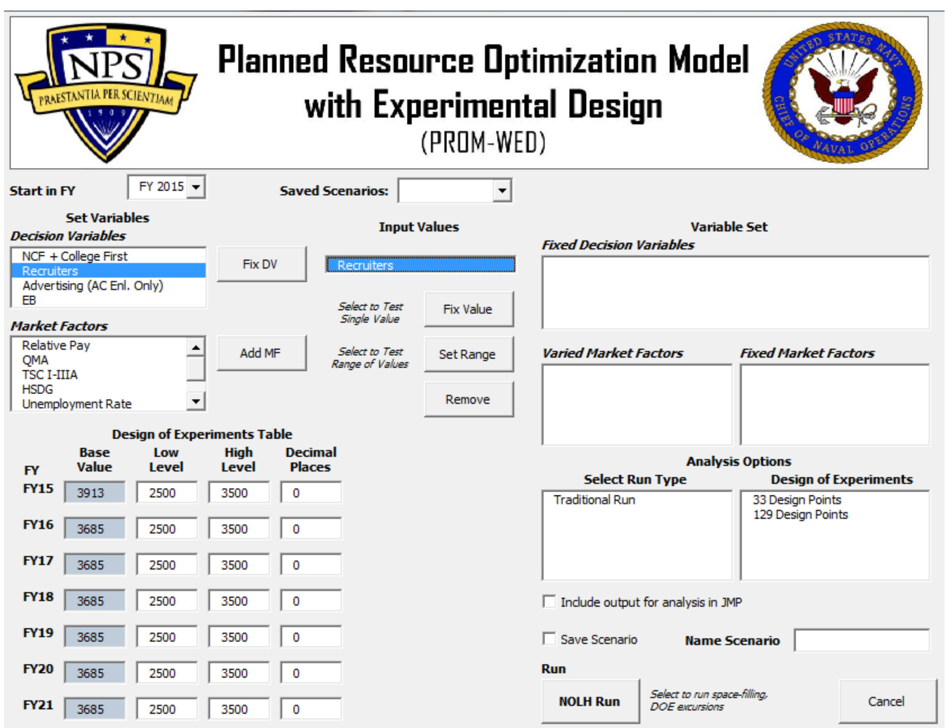


The variables are categorized as either “Decision Variables” or “Market Factors.” A decision variable can either be constrained (“Fixed”) or unconstrained (“Floated”). The title “Market Factors” is a blanket category that covers both market factors, as well as policy factors, as described in Chapter II.

A brief description of how a PROM-WED excursion is performed using the GUI is now presented. A detailed PROM-WED user manual can be found in Appendix C.

To constrain a decision variable, select the variable of interest and click on “Fix DV.” A constrained decision variable can either be fixed as a constant or tested over a range of values using the NOLH algorithm. If the user is interested in testing over a range, the desired lower and upper bounds of the range are inputted into the “Design of Experiments Table,” as shown in Figure 28.

Figure 28. Testing a Decision Variable over a Constrained Range

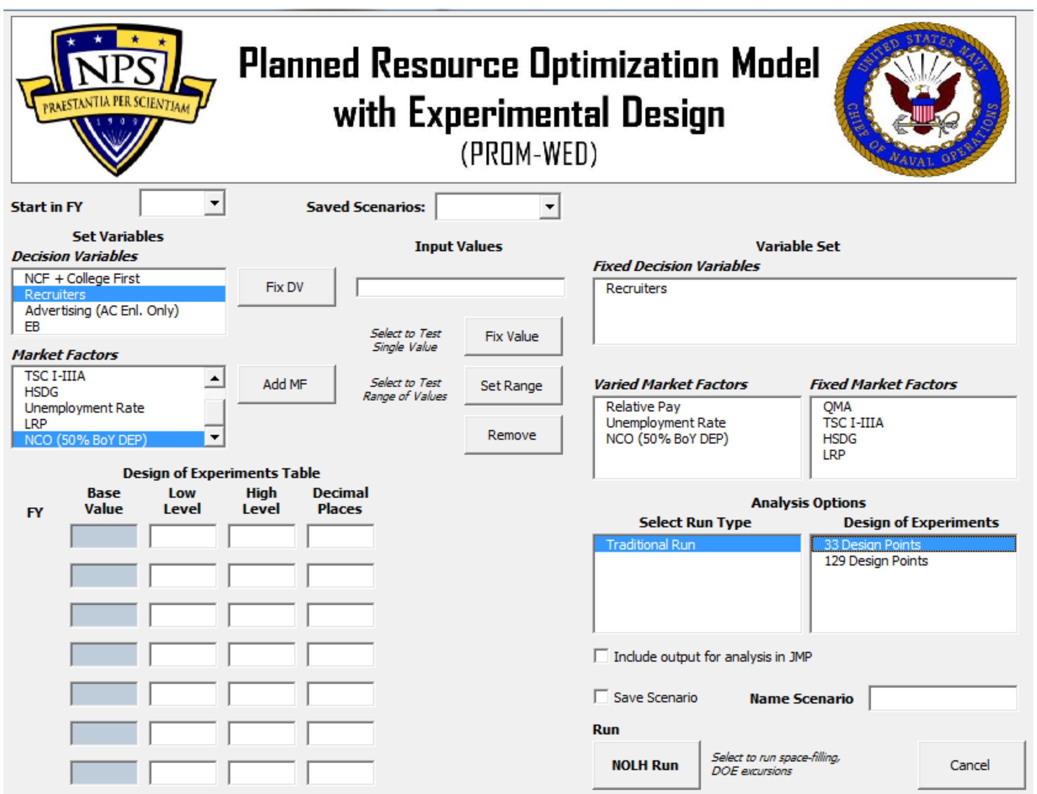


Number of recruiters is being tested over a range of 2,500 to 3,500 for each FY of this excursion.

Each “low level” and “high level” value of the “Design of Experiments Table” is linked to a NOLH worksheet. For example, the low and high values for FY 17 are linked to the NOLH worksheet for FY 2017, as shown previously in Figure 26.

A similar procedure is followed for each variable listed in the “Market Factors” category. The user must work through each variable in the “Market Factors” list, and choose whether it is kept constant (“Fix Value”), or tested over a range of values (“Set Range”). The NOLH DOE is complete once all variables listed in the “Market Factors” category are accounted for. Once the NOLH is fully populated, as shown in Figure 29, the user selects the “Run Type,” and the number of design points the NOLH is tested over. Currently PROM-WED has the capability to test the traditional run option. Further work is required for the capacity run option.

Figure 29. PROM-WED GUI when NOLH is Fully Populated



Selecting the “NOLH RUN” button executes the subroutine to begin growing the data. The 33-point design takes approximately two minutes to run on a standard modern personal computer (PC), whereas the 129-point design takes about five to ten minutes to run. Run times are dependent on factors such as the operating system and computational capacity of the computer. The result for each PROM-WED scenario is deposited to a worksheet for further analysis.

3. PROM-WED Decision Support Analysis

In addition to growing PRO model data using data farming, PROM-WED provides users with decision support capabilities to analyze the data grown by each excursion. PROM-WED offers two decision support capabilities: (1) automatically generated analysis and (2) data generated for further analysis requiring a statistical software package. In this section, PROM-WED’s decision support capabilities are discussed. The focus is on why each type of graph or table was chosen. Chapter IV has a detailed discussion dedicated to analyzing PROM-WED’s decision support capability.

a. Automatically Generated Decision Support Capability

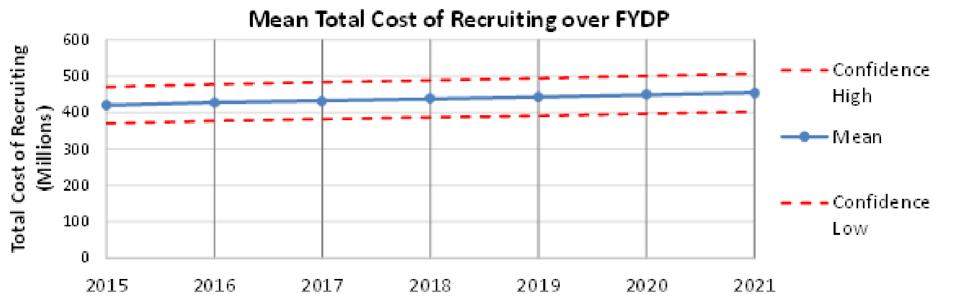
The purpose of PROM-WED’s automatically generated decision support analysis is to provide users with a tool capable of providing an at-a-glance understanding of the solution space of a completed PROM-WED excursion. PROM-WED’s “Decision Support Analysis” for the traditional run option provides users with a broad understanding of how variability in decision variables, controllable policy changes, and uncontrollable market factors affect the total cost of recruiting. Since the traditional run addresses the allocation of resources (i.e., the decision variables), the automatically generated decision support capability provides at-a-glance insights to decision makers regarding the optimal allocation of recruiting resources using the 33-point design. In the next section, further insights regarding variable interactions and the effects of the various market factors are explored using a commercial statistical software package.

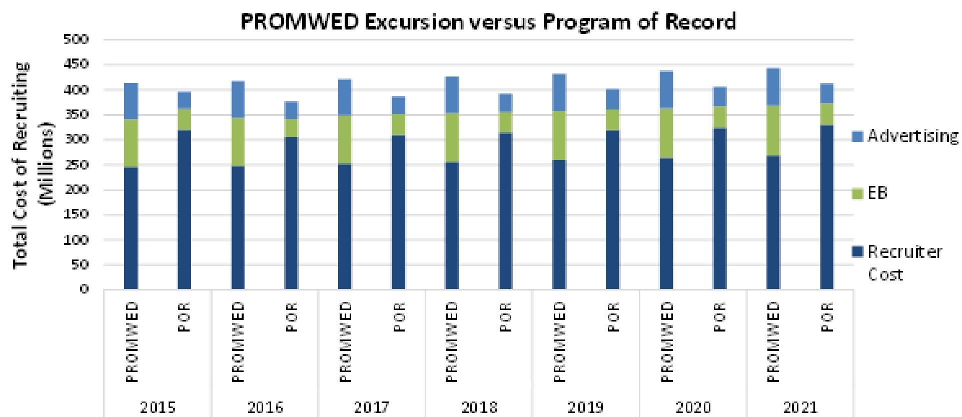
In an effort to provide as much relevant information as possible within an easily printed worksheet, Figures 30 and 31 show the two pages that comprise PROM-WED's automatically generated decision support capability for the traditional run option.

Figure 30. Traditional Run Decision Support Analysis, Page 1

PROM-WED
Decision Support Analysis

Traditional Run: 33 Design Points

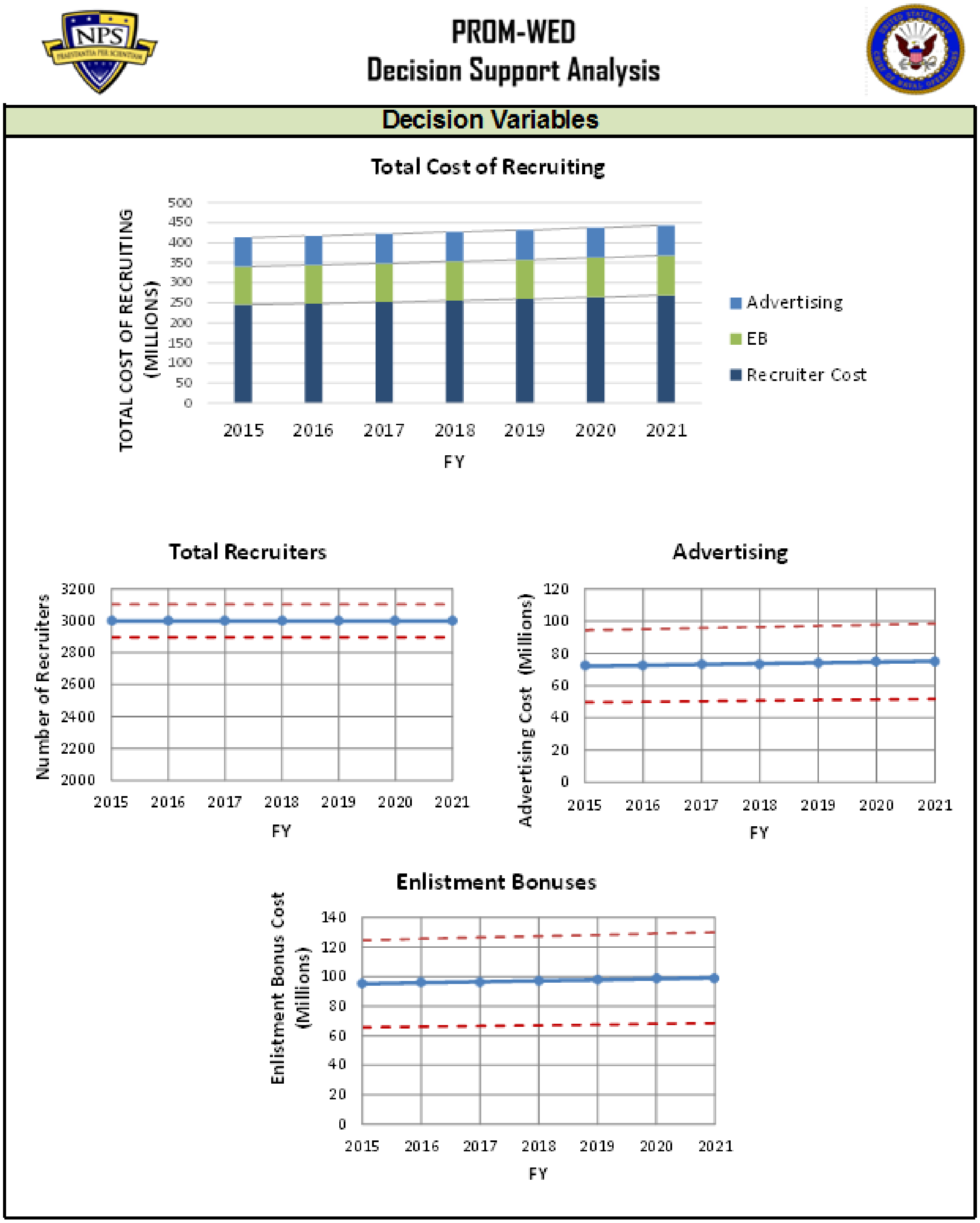




Scenario

		2015	2016	2017	2018	2019	2020	2021
NCO	high	40000	40000	40000	40000	40000	40000	40000
	low	30000	30000	30000	30000	30000	30000	30000
LRP	high	7.44	11.22	11.28	11.38	11.43	11.46	11.67
	low	7.44	11.22	11.28	11.38	11.43	11.46	11.67
HSDG	high	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	low	0.95	0.95	0.95	0.95	0.95	0.95	0.95
TSC	high	0.85	0.85	0.85	0.85	0.85	0.85	0.85
	low	0.7	0.7	0.7	0.7	0.7	0.7	0.7
UE	high	0.08	0.08	0.08	0.08	0.08	0.08	0.08
	low	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Rel Pay	high	1.2	1.2	1.2	1.2	1.2	1.2	1.2
	low	0.8	0.8	0.8	0.8	0.8	0.8	0.8
QMA	high	1883304	1873304	1863304	1853304	1843304	1833304	1823304
	low	1873304	1863304	1853304	1843304	1833304	1823304	1813304

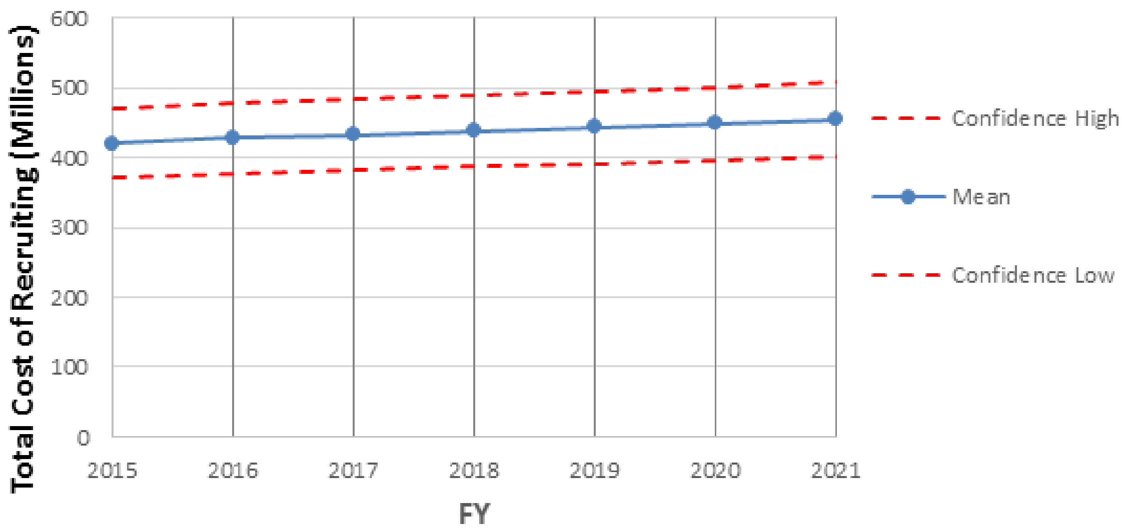
Figure 31. Traditional Run Decision Support Analysis, Page 2



The six graphs and one table make up the traditional run's decision support analysis. The purpose of each graph is now explained.

Starting in the top left, the “Mean Total Cost of Recruiting over FYDP” graph, also shown in Figure 32, shows the resulting mean total cost of recruiting for each FY.

Figure 32. Graph 1: Mean Total Cost of Recruiting over FYDP



The mean for each FY is represented by the blue dots. The red dashed lines represent the 95 percent confidence interval for each mean. Where “n” is the number of sample points. For example, n = 33 for the 33-point NOLH design, and so forth. Here we are treating each observation as an equally likely sample of possible recruiting scenarios. The 95 percent confidence intervals for all graphs shown in the automatically generated decision support analysis are calculated as follows:

(1) First, the sample standard deviation is calculated:

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

The Microsoft Excel formula STDEV.S() is used in PROM-WED.

(2) Next, since each scenario is independent, and it is assumed that the sample mean is approximately normally distributed, the margin of error at 0.05 significance level is calculated:

$$margin\ of\ error = z_{\alpha/2}\frac{s}{\sqrt{n}};$$
$$where{:}\ \alpha = 0.05\ and$$
$$z_{\alpha/2}\ is\ the\ 100(1-\alpha/2)\ percentile\ of\ a\ standard\ normal\ random\ variable$$

The Microsoft Excel formula CONFIDENCE.NORM() is used in PROM-WED.

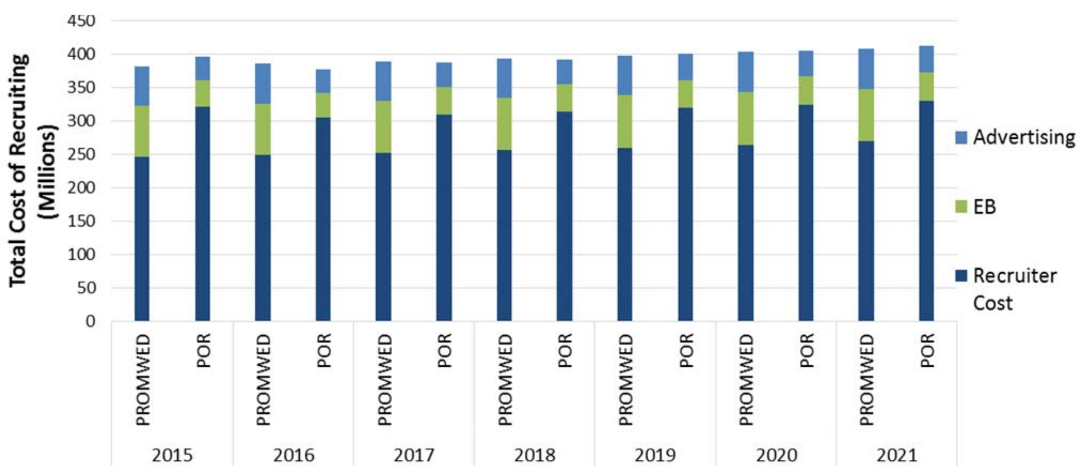
(3) Finally, the upper and lower confidence bounds are calculated:

$$\bar{x} \pm margin\ of\ error$$

The region between the two red dashed lines represents with 95 percent confidence the mean total cost of recruiting is somewhere within this range.

The second graph "PROM-WED Excursion versus Program of Record," also shown in Figure 33, compares the mean optimal allocation of recruiting resources that resulted from the PROM-WED excursion with the program of record.

Figure 33. Graph 2: PROM-WED Excursion versus Program of Record



The program of record (POR) is the resource allocation “recorded in the current Future Years Defense Program (FYDP) or as updated from the last FYDP by approved program documentation” (DAU, n.d.). Within the legacy PRO model the POR is fixed for each FY. PROM-WED only reports these fixed numbers (i.e., they are the same for each run and are not included in the DOE). Each bar of the stacked bar chart is divided into segments that represent the amount of resources allocated to each decision variable. A difference between a PROM-WED excursion and a POR conveys to an analyst that the Navy should consider allocating funds differently to optimize the allocation of recruiting resources. These insights support informed decisions such as adjusting the number of Sailors assigned to recruiting duty or modifying the amount of resources allocated to advertisements and enlistment bonuses. Education incentives were not included in the decision support analysis, but can be added if the Navy begins to allocate funds towards this resource again.

The scenario report, shown in Table 10, reports the high and low values of each market factor for this PROM-WED excursion.

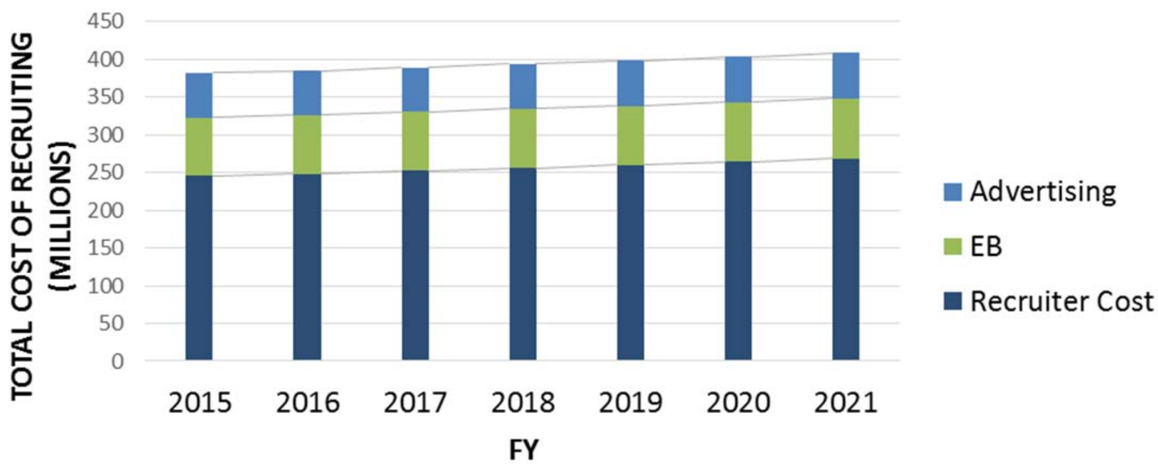
Table 10. PROM-WED Scenario Report

		2015	2016	2017	2018	2019	2020	2021
NCO	**high**	40000	40000	40000	40000	40000	40000	40000
	low	30000	30000	30000	30000	30000	30000	30000
LRP	**high**	7.44	11.22	11.28	11.38	11.43	11.46	11.67
	low	7.44	11.22	11.28	11.38	11.43	11.46	11.67
HSDG	**high**	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	low	0.95	0.95	0.95	0.95	0.95	0.95	0.95
TSC	**high**	0.85	0.85	0.85	0.85	0.85	0.85	0.85
	low	0.7	0.7	0.7	0.7	0.7	0.7	0.7
UE	**high**	0.08	0.08	0.08	0.08	0.08	0.08	0.08
	low	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Rel Pay	**high**	1.2	1.2	1.2	1.2	1.2	1.2	1.2
	low	0.8	0.8	0.8	0.8	0.8	0.8	0.8
QMA	**high**	1883304	1873304	1863304	1853304	1843304	1833304	1823304
	low	1873304	1863304	1853304	1843304	1833304	1823304	1813304

If the high and low values are equal, the market factor is fixed, such as NCO in the scenario shown in Table 10. If the market factor is tested over a range, the high and low values are not equal, such as assessing the effect of varying the percentage of high quality recruits (TSC) from 70 percent to 85 percent, also shown in Table 10.

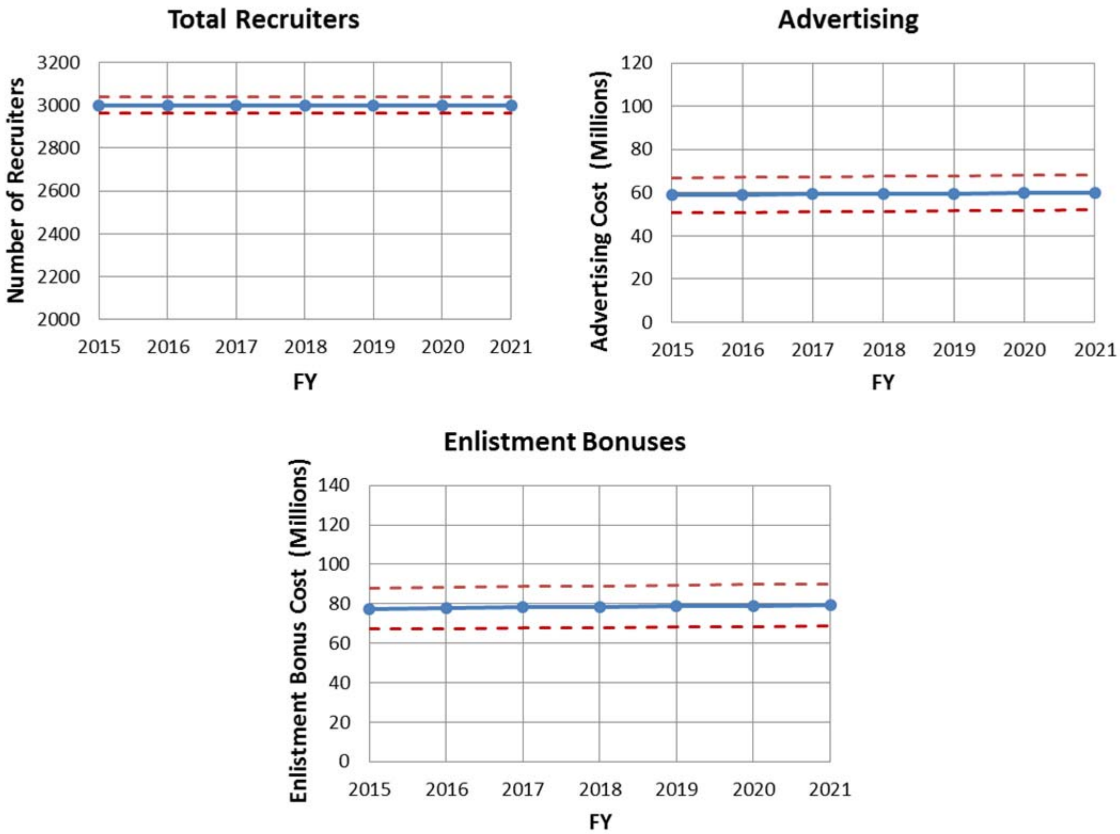
The focus of the second page is on how the decision variables vary. The “Total Cost of Recruiting” stacked bar chart shown in Figure 34 indicates how much money is allocated to each recruiting resource over a seven FY span.

Figure 34. Graph 3: Total Cost of Recruiting



The following three graphs, shown in Figure 35, represent how deviations in controllable and uncontrollable factors affect the amount of resources allocated to each decision variable. The blue dots represent the mean for each decision variable over each FY, and the red dashed lines represent the 95 percent confidence interval about that mean.

Figure 35. Graphs 4–6: Decision Variables



b. JMP Output

PROM-WED provides users with output results that are saved as an .xlsx file and can be further analyzed using any statistical software package. N1 analysts use JMP; hence PROM-WED's output is named "JMP output." JMP has modeling tools, such as partition trees and stepwise regression models, that are conducive for testing interactions between multiple variables while quantifying and visualizing how they affect the overall solution space.

PROM-WED's JMP output is color-coded by variable type, and is organized for ease of import into a data analysis package. A snap shot of the JMP output for one FY of a 33 design point PROM-WED excursion is shown in Figure 36.

Figure 36. JMP Output for a 33 Design Point

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Run #	FY	Total Cost of Recruiting	Advertising	EB	Education Incentive	Total Recruiters	Recruiter Cost	NCO	LRP	HSDG	TSC I-IIIA	Unemployment	Relative Pay	QMA
2	1	2015	403.8507	85.1535	70.625	0	2938	240.6322	36875	7.44	0.99	0.7	4.4	1.075	1823929
3	2	2015	402.5814	120.457	59.688	0	2625	214.9964	37500	7.44	0.99	0.7	8	0.975	1798929
4	3	2015	363.1557	6.9087	69.844	0	3406	278.963	37188	7.44	0.96	0.7	5.8	1.1875	1845804
5	4	2015	510.0452	157.0373	58.906	0	3500	286.6619	38125	7.44	0.97	0.7	7.5	0.8375	1861429
6	5	2015	562.9863	239.4061	72.969	0	2969	243.1712	34063	7.44	0.95	0.7	4.1	0.85	1814554
7	6	2015	302.3627	4.0595	60.469	0	2813	230.3942	31563	7.44	0.95	0.7	7.8	1.0125	1808304
8	7	2015	452.7505	89.7816	71.406	0	3469	284.1229	33750	7.44	0.99	0.7	5.9	0.8	1855179
9	8	2015	351.1139	0.84	61.25	0	3438	281.5839	32188	7.44	0.97	0.7	6.8	1.175	1864554
10	9	2015	299.6583	6.71	62.813	0	2719	222.6953	30000	7.44	0.97	0.7	5	1.0375	1877054
11	10	2015	324.1503	20.656	68.281	0	2781	227.7733	30938	7.44	0.98	0.7	6.6	0.875	1880179
12	11	2015	336.2882	6.0992	56.563	0	3250	266.186	31250	7.44	0.97	0.7	4.9	1.05	1817679
13	12	2015	387.5209	42.3748	79.219	0	3156	258.4871	34688	7.44	0.96	0.7	6.9	0.8625	1827054
14	13	2015	2904.1699	2618.4486	58.125	0	2688	220.1563	39688	7.44	0.96	0.7	4.6	0.9125	1883304
15	14	2015	374.174	62.1987	69.063	0	2875	235.4723	39375	7.44	0.96	0.7	6.4	1.1125	1870804
16	15	2015	497.6156	161.2907	55	0	3344	273.8849	36563	7.44	0.98	0.7	4.8	0.9375	1792679
17	16	2015	347.5317	9.0266	77.656	0	3094	253.4091	35625	7.44	0.98	0.7	6.5	1.1	1830179
18	17	2015	349.6849	29.0347	67.5	0	3000	245.7102	35000	7.44	0.97	0.7	6	1	1833304
19	18	2015	334.7533	12.0682	64.375	0	3063	250.8701	33125	7.44	0.95	0.7	7.6	0.925	1842679
20	19	2015	370.0413	10.8643	75.313	0	3375	276.424	32500	7.44	0.95	0.7	4	1.025	1867679
21	20	2015	456.8925	171.8391	65.156	0	2594	212.4574	32813	7.44	0.98	0.7	6.3	0.8125	1820804
22	21	2015	297.4717	9.1792	76.094	0	2500	204.7585	31875	7.44	0.97	0.7	4.5	1.1625	1805179
23	22	2015	323.6255	5.9053	62.031	0	3031	248.2492	35938	7.44	0.99	0.7	7.9	1.15	1852054
24	23	2015	568.4716	225.3926	74.531	0	3188	261.108	38438	7.44	0.99	0.7	4.3	0.9875	1858304
25	24	2015	304.7412	26.4097	63.594	0	2531	207.2975	36250	7.44	0.96	0.7	6.1	1.2	1811429
26	25	2015	2391.7261	2100.6177	73.75	0	2563	209.9184	37813	7.44	0.97	0.7	5.3	0.825	1802054
27	26	2015	458.5049	110.1519	72.188	0	3281	268.725	40000	7.44	0.97	0.7	7	0.9625	1789554
28	27	2015	380.9688	43.1628	66.719	0	3219	263.647	39063	7.44	0.96	0.7	5.4	1.125	1786429
29	28	2015	494.1179	183.0056	78.438	0	2750	225.2343	38750	7.44	0.98	0.7	7.1	0.95	1848929
30	29	2015	322.9417	26.7874	55.781	0	2844	232.9333	35313	7.44	0.98	0.7	5.1	1.1375	1839554
31	30	2015	356.2942	0.6333	76.875	0	3313	271.3459	30313	7.44	0.98	0.7	7.4	1.0875	1783304
32	31	2015	346.3979	17.0718	65.938	0	3125	255.9481	30625	7.44	0.98	0.7	5.6	0.8875	1795804
33	32	2015	311.9011	6.9257	80	0	2656	217.5354	33438	7.44	0.96	0.7	7.3	1.0625	1873929
34	33	2015	412.3618	109.5665	57.344	0	2906	238.0113	34375	7.44	0.96	0.7	5.5	0.9	1836429

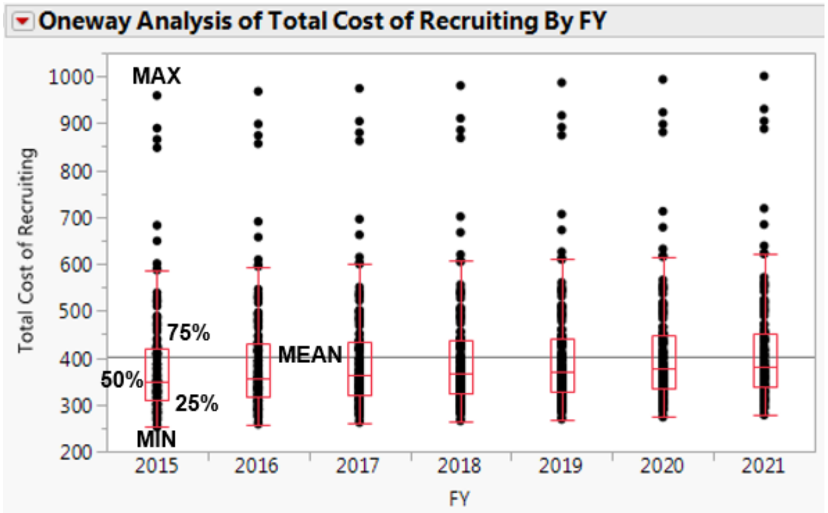
Blue represents the output: Total Cost of Recruiting, green represents the decision variables, orange represents policy factors, and red represents the environmental factors.

This thesis uses JMP Pro Version 12 to analyze PROM-WED data using six primary techniques: (1) oneway analysis graphs, (2) distributions and descriptive statistics, (3) partition trees, (4) stepwise regression models, (5) scatterplot matrices, and (6) contour plots (JMP Pro, 2015). The purpose of this section is to explain the principal techniques that are used in the analysis section. With many of these techniques additional analysis could be done. The analysis provided in this research is illustrative of what analysts can do with PROM-WED output.

(1) Oneway Analysis Graphs

A oneway analysis graph is used to gain a quantifiable understanding of the spread of the total cost of recruiting data over each FY. The setup and structure of this graph is shown in Figure 37.

Figure 37. Oneway Analysis of Total Cost of Recruiting by FY Structure



Quantiles

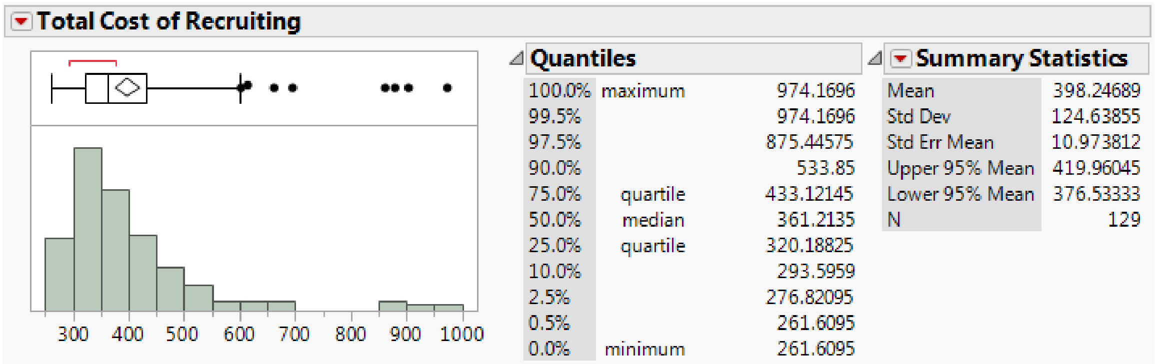
Level	Minimum	10%	25%	Median	75%	90%	Maximum
2015	251.8643	283.3929	309.1051	349.9401	421.2093	521.9235	959.1079
2016	258.138	289.8711	315.9455	356.89	428.4688	529.2777	968.0586
2017	261.6095	293.5959	320.1883	361.2135	433.1215	533.85	974.1696
2018	265.1709	297.4278	324.5511	365.861	437.8086	538.5172	980.3789
2019	268.7332	301.3375	329.0443	370.5412	442.3917	543.1901	986.5974
2020	272.8857	305.6795	334.2964	375.5285	447.5582	548.4681	993.3847
2021	277.2888	310.3785	339.8189	380.7692	453.0851	554.0022	1000.43

The boxplots that overlay the data represent the information presented in the "Quantiles" table. From Figure 37, it is evident that more than 50 percent of the data (i.e., the median) is less than the grand mean. The grand mean is represented by the horizontal line labeled "mean," and the median is represented by the "50%" label. The median is a useful estimator that provides safety against outliers, whereas the mean is highly influenced by extreme values, both high and low.

(2) Distributions and Descriptive Statistics

Histograms provide insight regarding the nature of the output data. For example, Figure 38 shows that the total cost of recruiting is highly skewed to the right. The long tail indicates that there are some particularly large outliers, but the majority of the data does not follow this trend.

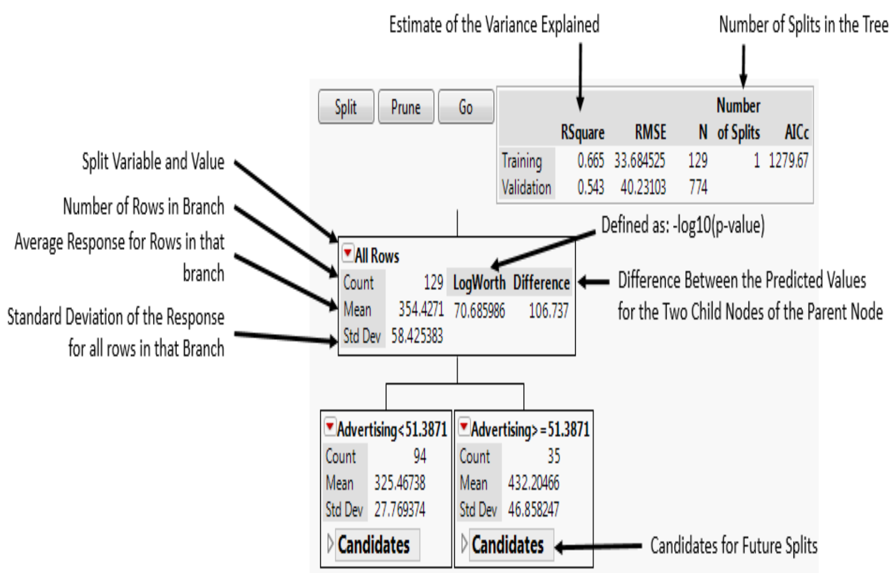
Figure 38. Distribution and Descriptive Statistics Structure



(3) Partition Tree

The setup and structure for a partition tree is shown in Figure 39.

Figure 39. JMP Partition Tree Structure



Adapted from Borozny, 2015, p. 37; Lane, n.d.

A story can be told from interpreting a partition tree. For instance, the tree shown in Figure 39 conveys the following message:

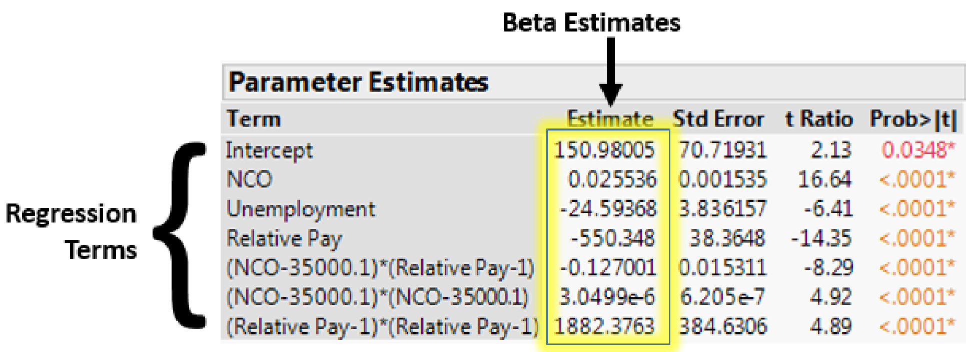
The mean total cost of recruiting will be approximately $354 million. Since advertising is the first child of the parent node, advertising is the dominant

decision variable, where 66.5 percent of the variance for the total cost of recruiting can be explained. If the cost of advertising remains below $51.4 million, then the average cost of recruiting is approximately $325 million. If the cost of advertising equals to or exceeds $51.4 million, then the average cost of recruiting increases to $432 million.

(4) Stepwise Regression Model

Stepwise regression can be used to formulate a prediction model for total cost of recruiting, as shown in Figure 40.

Figure 40. Stepwise Regression Structure



Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	150.98005	70.71931	2.13	0.0348*
NCO	0.025536	0.001535	16.64	<.0001*
Unemployment	-24.59368	3.836157	-6.41	<.0001*
Relative Pay	-550.348	38.3648	-14.35	<.0001*
(NCO-35000.1)*(Relative Pay-1)	-0.127001	0.015311	-8.29	<.0001*
(NCO-35000.1)*(NCO-35000.1)	3.0499e-6	6.205e-7	4.92	<.0001*
(Relative Pay-1)*(Relative Pay-1)	1882.3763	384.6306	4.89	<.0001*

The beta estimates and regression terms shown in Figure 40 are used to formulate the prediction model shown in Figure 41.

Figure 41. Prediction Model for Total Cost of Recruiting Fit Using Stepwise Regression

Prediction Expression

150.980052850998

+ 0.02553596931337 * NCO

+ -24.593679044673 * Unemployment

+ -550.34801858165 * Relative Pay

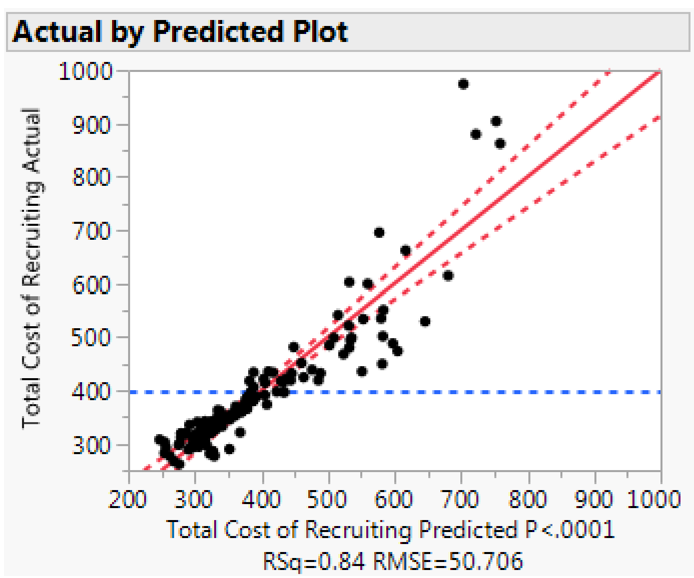
+ (NCO - 35000.0620155039) * ((Relative Pay - 1) * -0.1270005027034)

+ (NCO - 35000.0620155039) * ((NCO - 35000.0620155039) * 0.00000304992539)

+ (Relative Pay - 1) * ((Relative Pay - 1) * 1882.37625427676)

Actual by predicted plots, as shown in Figure 42, demonstrate the relationship between the actual data and the model fit using stepwise regression. In this case, the closer the points are to the solid red line the better the fit.

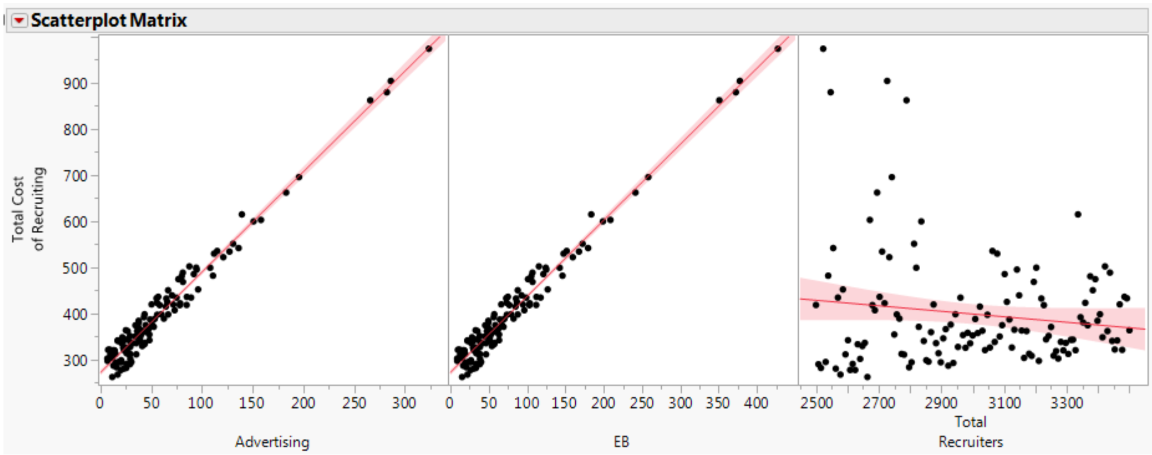
Figure 42. Actual by Predicted Plot.



(5) Scatterplot Matrices

Each panel of the scatterplot matrix in Figure 43 shows the relationship between a decision variable, on the x-axis, and the total cost of recruiting, on the y-axis.

Figure 43. Scatterplot Matrix Structure



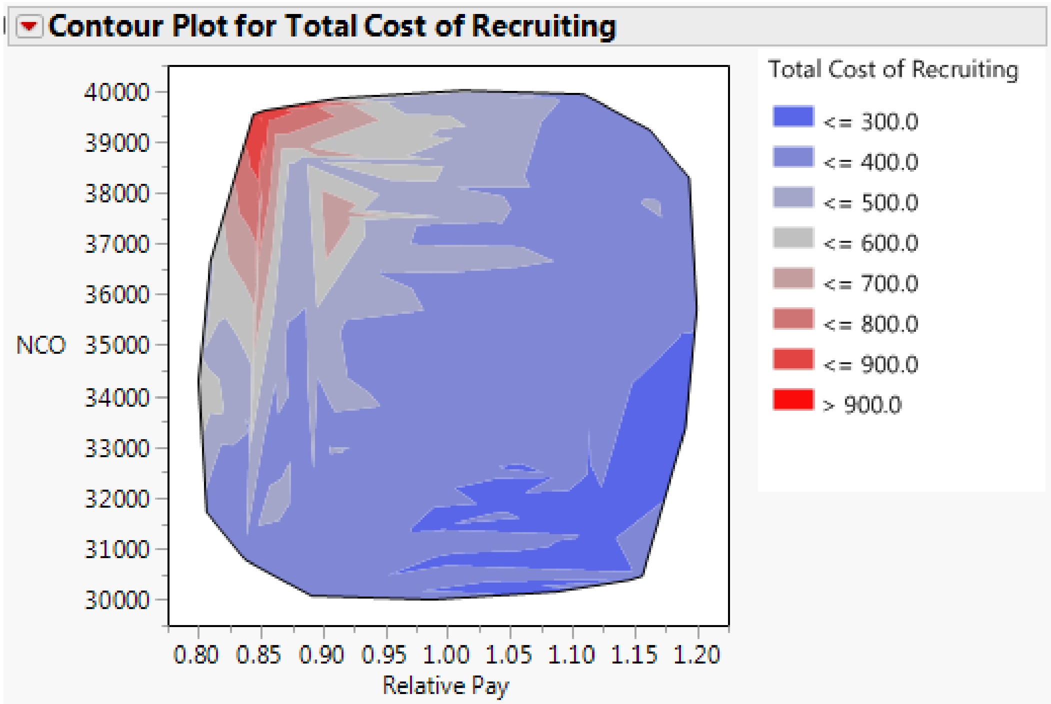
The dark red line within the shaded red region indicates a trend line fit in JMP. From these scatterplot matrices, trends can be deduced to help analysts further understand the relationships amongst the model's variables. For example, both advertising and EB show a distinct, upward linear trend in relation to the total cost of recruiting. The narrow confidence bands around the trend line also indicate this is a strong relationship. Whereas, the total number of recruiters has only a minor, downward trend. The wider confidence interval around the trend line for this plot indicates that the total number of recruiters has minimal effect on the total cost of recruiting for this scenario.

(6) Contour Plots

Contour plots provide insights similar to the "capture the flag" example previously shown in Figure 22, where the multi-level full factorial DOE provides a detailed understanding of the solution space. The contour plot in Figure 44 shows the relation between relative pay and accession mission on the total cost

of recruiting. Note that other factors are changing too, so it is important to look for broad trends, not local features.

Figure 44. Contour Plot Structure



The color variations in Figure 44 represent the total cost of recruiting at different combinations of relative pay and new accession mission values. The diagonal nature of the plot indicates there is an interaction between relative pay and the new accession mission. To minimize the total cost of recruiting, it is recommended that the Navy stays within the dark blue regions if the higher relative pay is feasible.

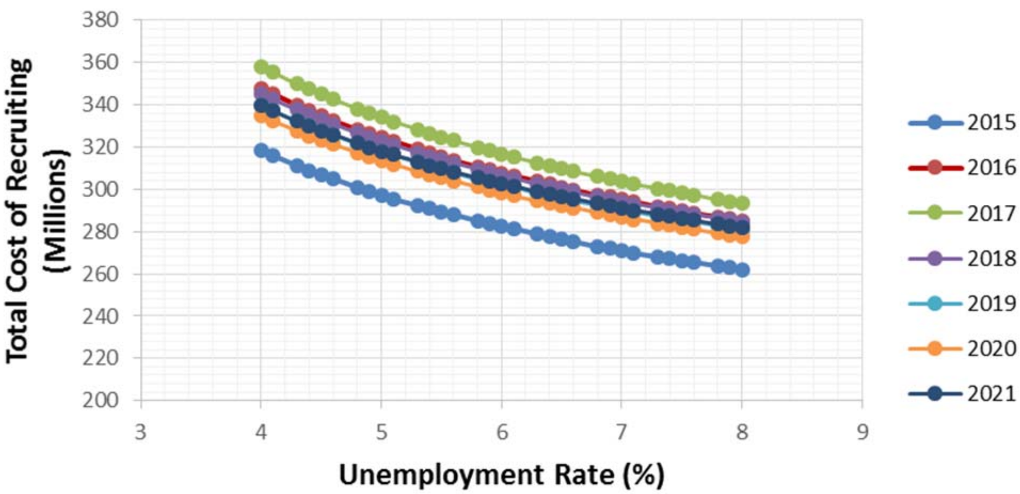
c. Building PROM-WED: Collaboration with Future Users

To ensure the practicality and future usability of this research, analysts at N1 played a critical role in the creation of the PROM-WED tool, specifically in regards to the GUI development and the decision support capabilities. A future PROM-WED user had hands-on time with the tool to test its limitations and

identify potential glitches. Through this meeting, we identified problems with the save scenario capability and identified sources of potential confusion that needed clarification and were subsequently addressed within the PROM-WED User Manual. In addition to the GUI, N1 analysts were involved in the development of PROM-WED's decision support capability. For instance, the JMP output color-coding and the scenario report were added to the automatically generated decision support capability based on feedback from N1 analysts.

As with any new tool, it may take time for N1 analysts to become accustomed to using PROM-WED. For example, it was requested that a graph be added to the automatically generated decision support capability that displayed how unemployment rate effects the total cost of recruiting over each FY. An example of this graph is shown in Figure 45. The parameter inputs for the PROM-WED excursions shown in Figures 45 and 46 can be found in Appendix D.

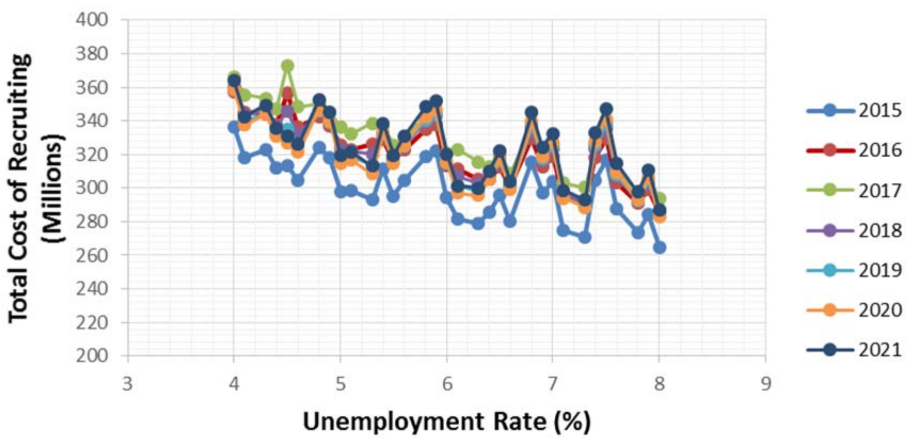
Figure 45. Effect of Unemployment Rate on Total Cost of Recruiting



As expected, when the unemployment rate is low, the cost of recruiting is high, and as unemployment rate increases the cost of recruiting decreases. However, PROM-WED is capable of testing uncertainties in multiple variables,

not just one. When more than one variable is tested over a range, the graph becomes difficult to interpret. For example, Figure 46 is a PROM-WED excursion with the same input parameters as the PROM-WED excursion shown in Figure 45 except the number of recruiters is bounded from 2,500 to 3,500, instead of fixed at 3,913 as shown in Figure 45.

Figure 46. Effect of Varying Unemployment Rate and Number of Recruiters on Total Cost of Recruiting



From Figure 46, it is evident that bounding the number of recruiters does affect the total cost of recruiting. However, it is difficult to discern any valuable insights from Figure 46 regarding the interactions that are occurring between the varied number of recruiters and the unemployment rate on the total cost of recruiting. This example only varied two variables, whereas excursions that are explored in the next section vary up to six variables.

Examples such as this one demonstrate that through the implementation of DOE techniques, PROM-WED delivers results that provide valuable insights into the optimal allocation of recruiting resources. However, this added capability challenges the legacy analysis methods used to study legacy PRO model outputs.

IV. ANALYSIS

Through two test case examples, this chapter showcases PROM-WED's ability to deliver comprehensive insights into the optimal allocation of recruiting resources. The chapter begins with the introduction of the two test case examples, referred to as Test Case 1 and Test Case 2. These examples are first analyzed through PROM-WED's automatically generated decision support capabilities, and further explored using an array of statistical modeling and graphing methods in JMP. Finally, a modified version of Test Case 1 is used to compare the number of runs required for a full factorial DOE to the NOLH designs used in PROM-WED.

A. TEST CASES

To demonstrate PROM-WED's capabilities, N1 formulated three separate scenarios to model best case, worst case, and most likely situations for Navy recruiting. These scenarios are found in Appendix E. Rather than running three separate scenarios, PROM-WED can test this broad spectrum of possibilities and uncertainties using a single data farming run.

Test Case 1 explores uncertainties in economically driven market factors (i.e., relative pay and unemployment rate). Test Case 2 adds two additional degrees of uncertainty to Test Case 1 in the form of policy factor changes (i.e., QMA and recruit quality). All market factors not listed in the tables remain at their default values from the legacy PRO model. The scenario reports for each run are available in Appendix D.

a. Test Case 1

Test Case 1 covers a broad spectrum of economic uncertainties that represent best case, worst case, and most likely scenarios for Navy recruiting. For example, a low unemployment rate, relative pay favoring the civilian sector, and a high recruiting accession mission are challenging conditions for Navy

recruiting. On the other hand, a high unemployment rate, relative pay favoring the military, and a low recruiting accession mission would be favorable conditions for Navy recruiting. The input values for Test Case 1 are shown in Table 11 and can be used to answer a question such as:

What is the optimal allocation of recruiting resources that is robust to a broad range of economic uncertainties?

Table 11. Test Case 1 Input Variables

Variable Type	Variable Name	Value Low	Value High
Decision Variable	Recruiters	2,500 recruiters	3,500 recruiters
Market Factor	Unemployment Rate	4.0%	8.0%
Market Factor	Relative Pay	0.80	1.20
Policy Factor	Recruiting Mission (NCO)	30,000 recruits	40,000 recruits

For additional scenario details, refer to Appendix D.

b. Test Case 2

Test Case 2 maintains the foundation of Test Case 1, but adds the effects of varying two policy factors: (1) percentage of high quality recruits, and (2) qualified military available. Test Case 2's input variables are shown in Tables 12 and 13, and can be used to answer a question such as:

What is the optimal allocation of recruiting resources if the Navy desires to increase the percentage of high quality recruits from 70 percent to 85 percent? Due to uncertainties in the current fiscal environment, the unemployment rate may fluctuate between 4 to 8 percent, and the ratio of relative pay may vary between 0.8 and 1.2. In addition, since marijuana has been legalized for recreational use in many states nationwide, drug-use amongst 18–24 year-olds is expected to increase. An increase in drug-use amongst this age group means fewer young adults qualify for military service. Test Case 2 models the effect of an annual decrease of 10,000 qualified military available due to pre-service drug-use.

Table 12. Test Case 2 Input Variables

Variable Type	Variable Name	Value Low	Value High
Decision Variable	Production Recruiters	2,500 recruiters	3,500 recruiters
Market Factor	Unemployment Rate (UE)	4.0%	8.0%
Market Factor	Percentage of High Quality Recruits (TSC I-III)	70%	85%
Market Factor	Relative Pay	0.8	1.2
Market Factor	Qualified Military Available (QMA)	*See Table 13	
Policy Factor	Recruiting Mission (NCO)	30,000 recruits	40,000 recruits

Since Test Case 2 models the cumulative effects that the legalization of marijuana may have on the nation's QMA, the input values for QMA will decrease by 10,000 each FY. The QMA input values for Test Case 2 are shown in Table 13.

Table 13. Traditional Run 2 QMA Input Values

FY	QMA Value Low	QMA Value High
2015	1,873,304	1,883,304
2016	1,863,304	1,873,304
2017	1,853,304	1,863,304
2018	1,843,304	1,853,304
2019	1,833,304	1,843,304
2020	1,823,304	1,833,304
2021	1,813,304	1,823,304

For more information regarding Test Case 2 parameter inputs, refer to Appendix D.

B. DECISION SUPPORT ANALYSIS

As explained in Chapter III, PROM-WED automatically generates a selection of graphs to provide decision-makers with an "at-a-glance" understanding of the solution space. The 33-point design grows a sufficient

amount of data for basic statistical analysis in under two minutes. Since the purpose of the decision support analysis is to provide a quick understanding of the solution space, only the 33-point NOLH design is analyzed in this section. This type of analysis would be appropriate for testing excursions during a time constrained meeting, working group, or whenever basic analysis needs to be generated quickly. The 129-point NOLH grows more data, requiring a longer run time and more time is needed for adequate analysis. The 129-point NOLH is used in the JMP analysis section.

1. Test Case 1

Some major insights that are gained from Test Case 1's automatically generated decision support capability are now discussed. Figure 47 demonstrates that in an uncertain economic environment, the mean total cost of recruiting in FY 2017 will be within \$350 million to \$450 million, with 95 percent confidence.

Figure 47. Test Case 1: Mean Total Cost of Recruiting over FYDP

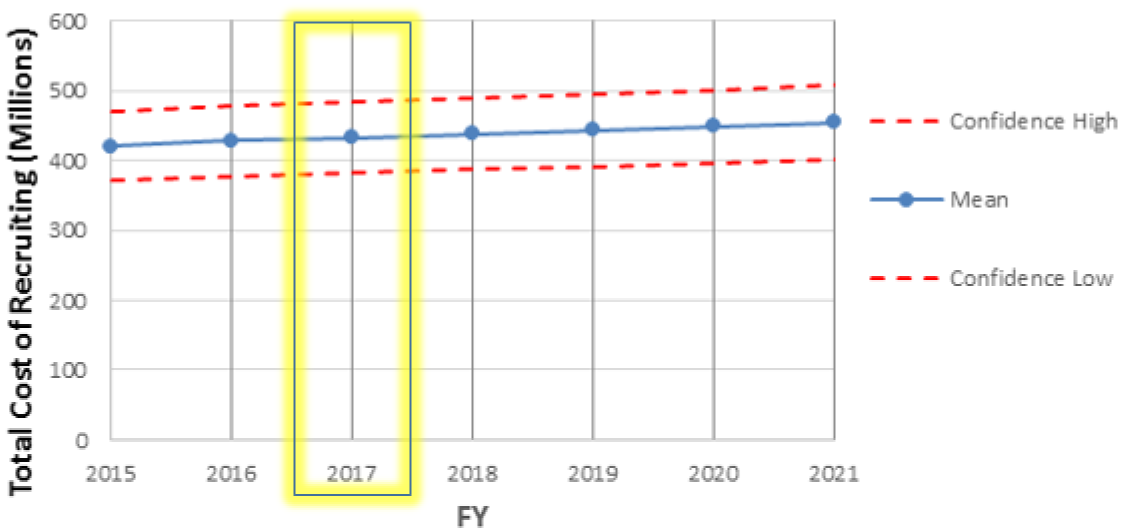
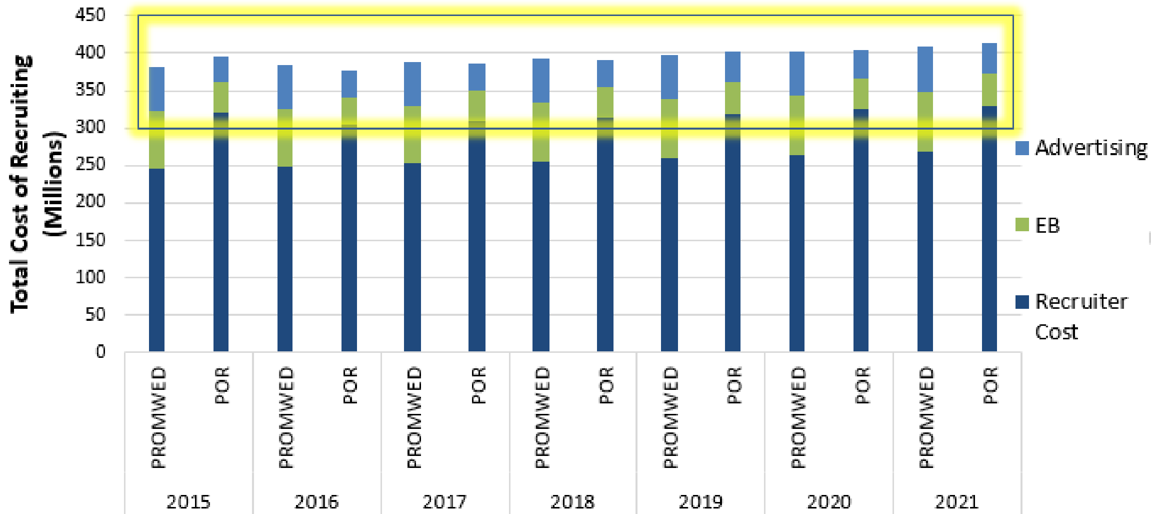


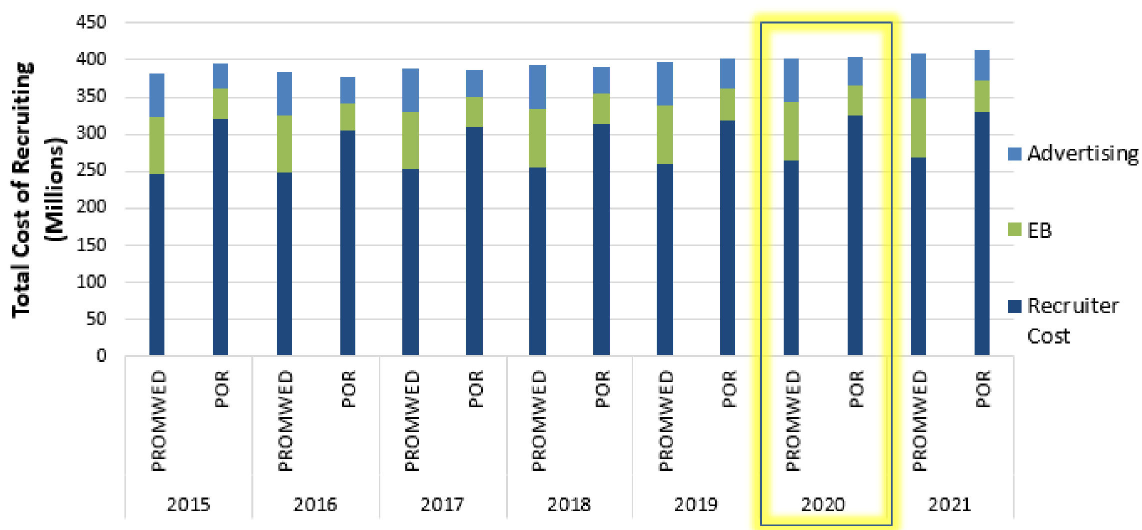
Figure 48 indicates that on average, the optimal cost of recruiting for each FY complements the program of record (POR) budget estimate.

Figure 48. Test Case 1: PROM-WED Excursion versus POR



The graph shown in Figure 48 can also inform decisions to redistribute funds to optimize the allocation of resources to advertisements, enlistment bonuses, and recruiters. For example, in the same graph, now labeled Figure 49, informed recommendations can be made to distribute resources differently in order to optimize the allocation of recruiting resources.

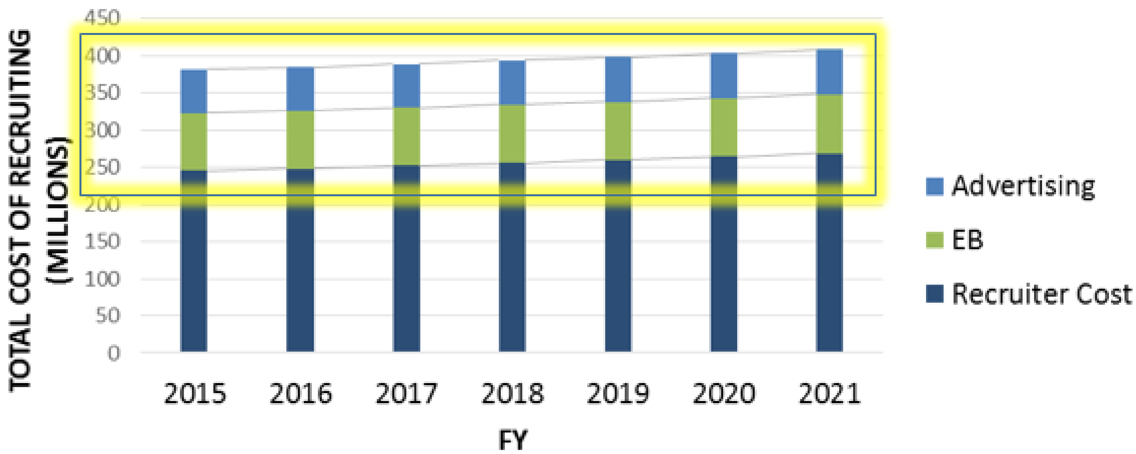
Figure 49. Test Case 1: PROM-WED versus POR



Dependent upon FY, if the dark blue bar is higher for POR than PROM-WED, this indicates that in order to optimize the allocation of recruiting resources, less resources need to be allocated to recruiters. Less funding allocated to recruiters means less recruiters are required in the field. The same convention goes for enlistment bonuses and advertisements. For example, in FY 2020 less funds should be allocated to recruiting and more funds should be allocated to enlistment bonuses and advertisements.

Figure 50 shows that the optimal allocation of recruiting resources appears to sustain a consistent trend amongst the seven FYs with only a minor upward trend, most likely due to inflation rates.

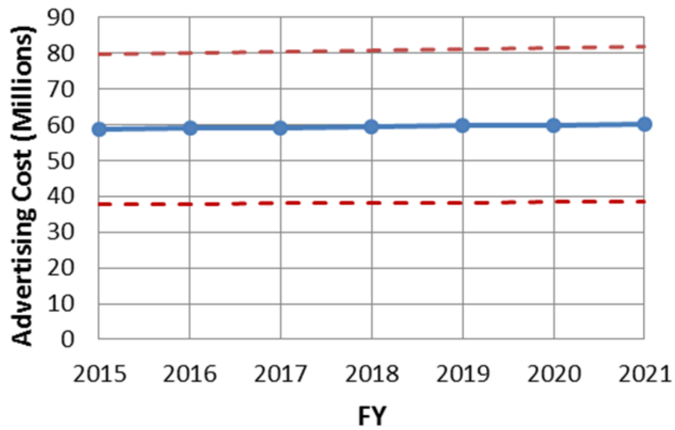
Figure 50. Test Case 1: Resource Allocation Breakdown



Insights gained through Figures 48 and 50 indicate there is evidence to believe that the total cost of recruiting is robust to uncertainties in the economic environment. However, to optimize the allocation of resources, more resources need to be allocated to enlistment bonuses and advertisements, as shown previously in Figure 49.

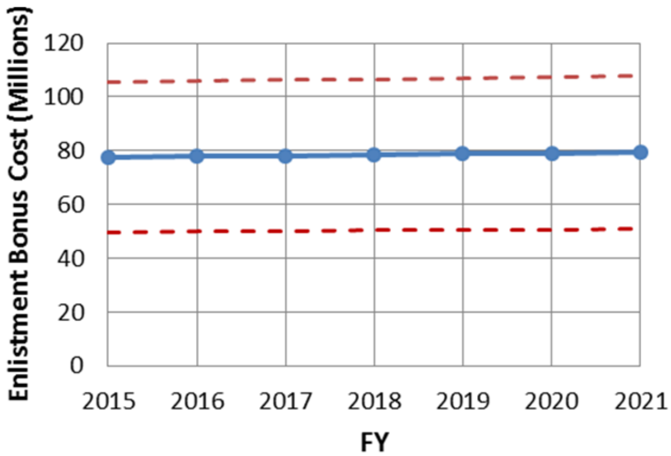
Figure 51 indicates that, with 95 percent confidence, the optimal allocation of resources to advertising over the seven FY span is consistently maintained within the range of approximately $40 million to $80 million.

Figure 51. Test Case 1: Advertising



Similar to the insights gained from Figure 51, Figure 52 demonstrates that with 95 percent confidence, the optimal allocation of resources to enlistment bonuses over the seven FY span consistently maintains a range of $50 million to $110 million.

Figure 52. Test Case 1: Enlistment Bonuses



2. Test Case 2

The effects of a shrinking QMA pool and an increased requirement for recruit quality is analyzed through the comparison of Test Case 1 and Test Case 2.

From Figure 53, there is evidence to believe that the Navy can expect the total cost of recruiting to increase by approximately $50 million as the need for high quality recruits increases, and the QMA pool shrinks. Without these policy influences, the 95 percent confidence interval increased from $350 million to $450 million in Test Case 1, to approximately $400 million to $500 million in Test Case 2.

Figure 53. Test Case 2: Mean Total Cost of Recruiting over FYDP

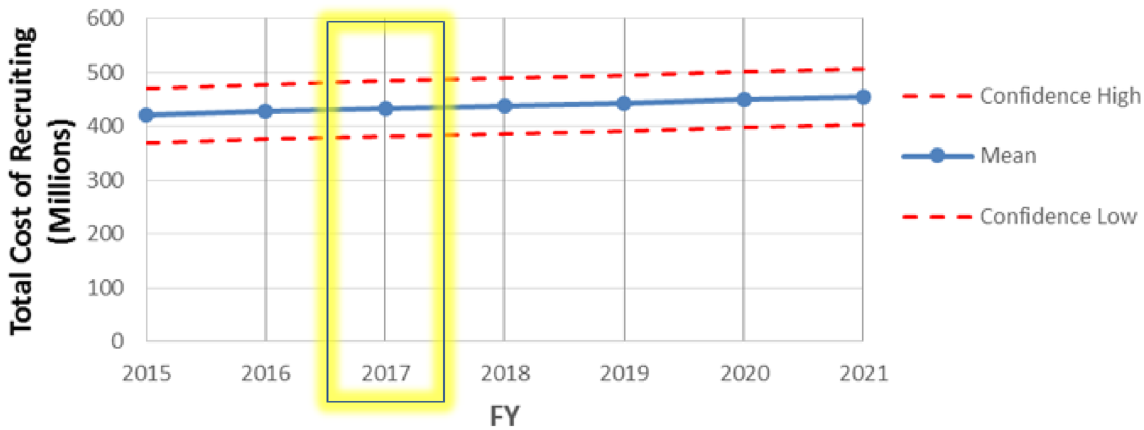
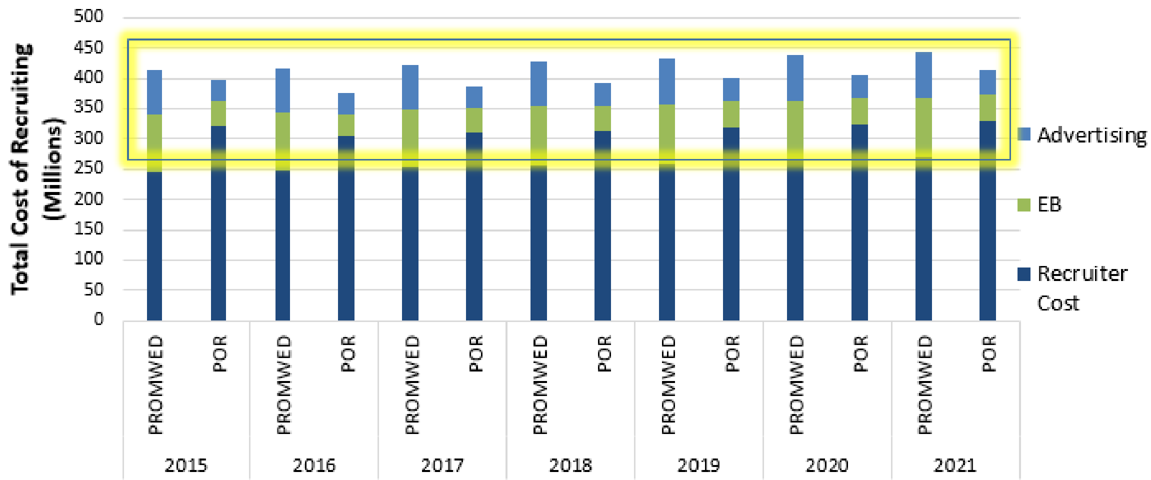


Figure 54 indicates that the total cost of recruiting is expected to exceed the program of record for every FY.

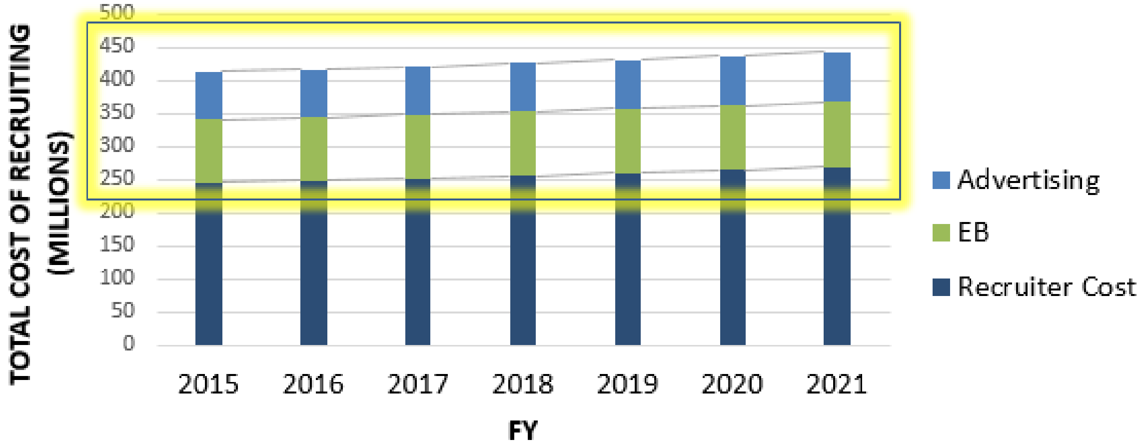
Figure 54. Test Case 2: PROM-WED Excursion versus POR



To optimize the allocation of recruiting resources, there appears to be a consistent trend amongst all seven FYs that an excess of resources was allocated to recruiters in the POR, while more resources should be allocated to advertisements and enlistment bonuses instead.

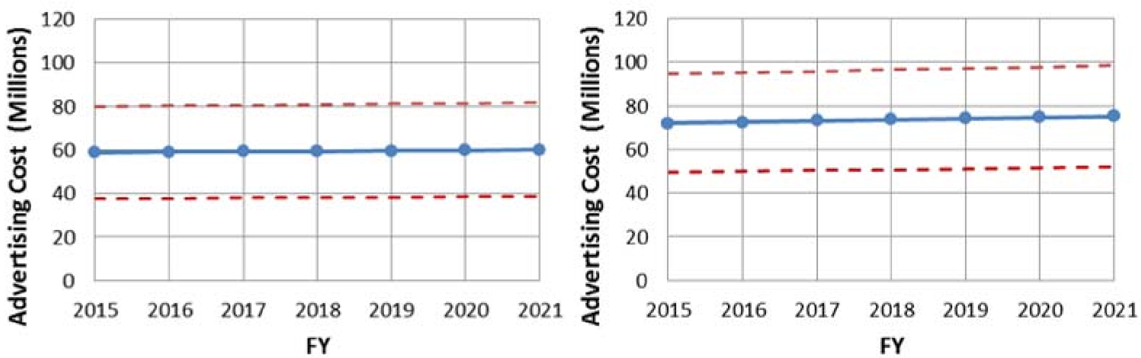
Due to the addition of QMA uncertainties and recruit quality policy changes, Figure 55 indicates that the average cost of recruiting is expected to increase by approximately $50 million over the seven FY span. This is a noticeable increase over the trend previously shown for Test Case 1 in Figure 50.

Figure 55. Test Case 2: Resource Allocation Breakdown



Figures 56 and 57 juxtapose results for advertisement and enlistment bonus resource allocations for Test Case 1 and Test Case 2.

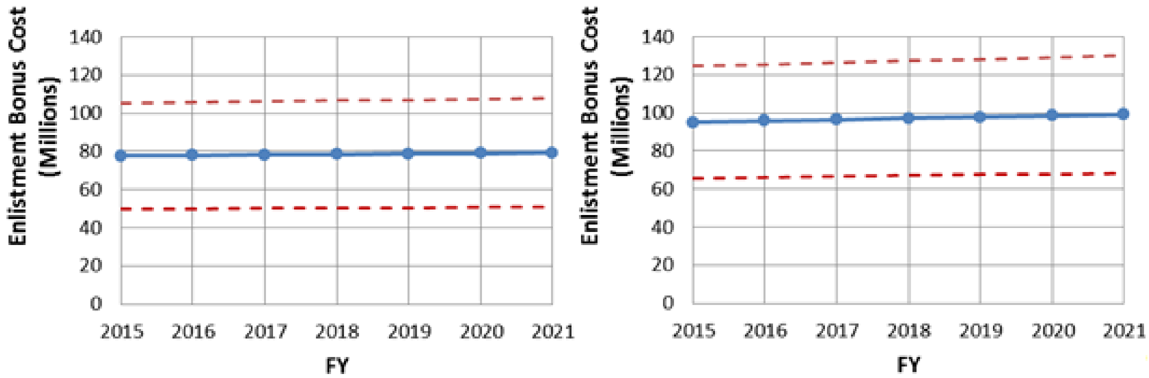
Figure 56. Resources Allocated to Advertising



Left: Test Case 1, right: Test Case 2.

Figure 56 indicates that the cost of advertising will increase by an average of approximately $10 million each FY.

Figure 57. Resources Allocated to Enlistment Bonuses



Left: Test Case 1, right Test Case 2.

Figure 57 indicates a similar trend for enlistment bonuses. These graphs show that an additional $20 million will be required for enlistment bonuses each FY due to the addition of QMA uncertainties and proposed recruit quality changes.

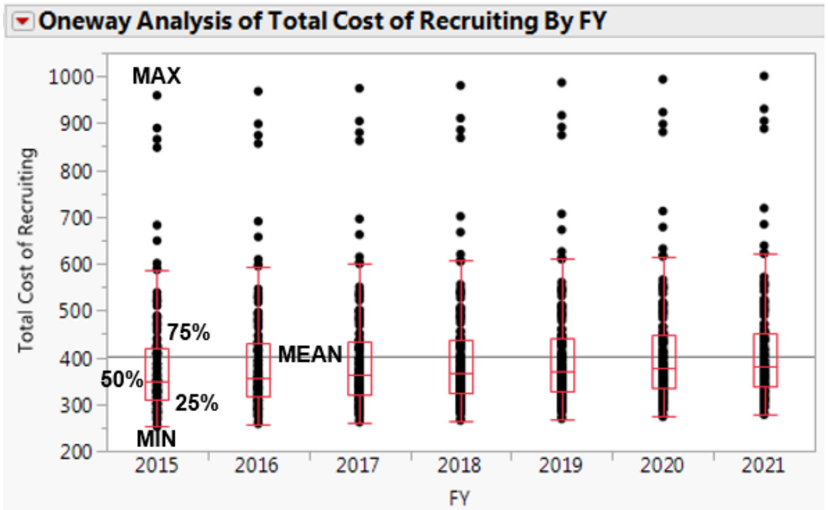
C. GRAPHICAL AND STATISTICAL ANALYSIS IN JMP

Valuable insights can be found through analyzing variable interactions and uncertainties that shape the robust solution space. However, analyzing and visualizing variable interactions in Microsoft Excel is difficult due to the software's limited statistical capability. Analysts will need to use a statistical software package to take full advantage of the data grown by PROM-WED. Test Case 1 and Test Case 2 are now analyzed using JMP.

1. Test Case 1

To gain an initial understanding of the data, Figure 58 shows the spread of data and provides quantile metrics for each FY. From Figure 58, it is evident that over 50 percent of the data, indicated by the median, generated for each FY is below the grand mean total cost of recruiting for each FY.

Figure 58. Total Recruiting By FY with Interquartile Ranges

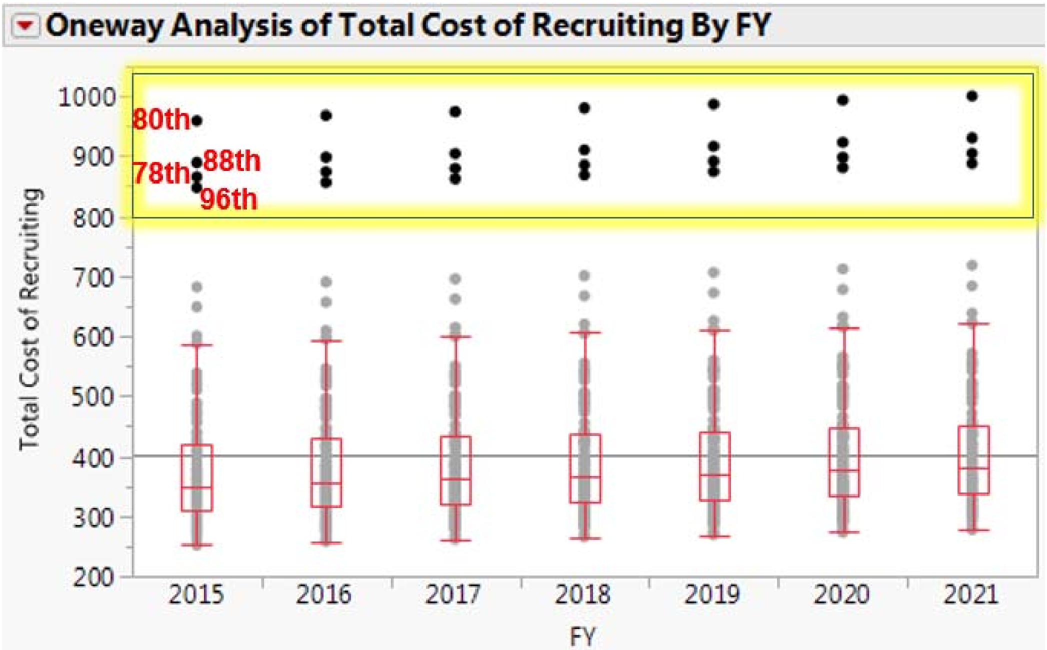


Quantiles

Level	Minimum	10%	25%	Median	75%	90%	Maximum
2015	251.8643	283.3929	309.1051	349.9401	421.2093	521.9235	959.1079
2016	258.138	289.8711	315.9455	356.89	428.4688	529.2777	968.0586
2017	261.6095	293.5959	320.1883	361.2135	433.1215	533.85	974.1696
2018	265.1709	297.4278	324.5511	365.861	437.8086	538.5172	980.3789
2019	268.7332	301.3375	329.0443	370.5412	442.3917	543.1901	986.5974
2020	272.8857	305.6795	334.2964	375.5285	447.5582	548.4681	993.3847
2021	277.2888	310.3785	339.8189	380.7692	453.0851	554.0022	1000.43

The outliers in Figure 58, highlighted below in Figure 59, are worth examining further to determine if there is a common cause for the four unusual data points. Using JMP, the highlighted sixteen data points are lassoed (i.e., selected) to reveal that the 78th, 80th, 88th, and 96th runs for each scenario caused these results over each FY. The run numbers represent four of the 129 different scenarios built using PROM-WED’s 129-point NOLH DOE. Since each FY uses the same NOLH DOE, the 80th run for each FY of Test Case 1 is tested over the same input market factors and number of recruiters. The same convention applies for the 78th, 88th, and 96th runs as well.

Figure 59. Outliers for Each FY



The upward trend occurs due to yearly changes, such as inflation rates, elasticities, or input values from the legacy PRO model. The input variables for each run highlighted in Figure 59 are shown in Table 14.

Table 14. Test Case 1 Input Variables for Output Outliers

	Run #			
	78	80	88	96
Recruiters	2547	2523	2727	2789
NCO	39531	39688	39453	39609
UE	7.0	5.9	5.1	5.1
Relative Pay	0.84375	0.878125	0.85	0.853125

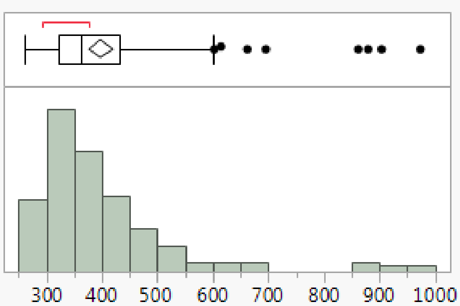
The most extreme total cost of recruiting outlier, resulting from the 80th run, tested an excursion where the Navy had a very low number of recruiters in the field (just over 2,500 recruiters), the new accession mission was extremely high (almost at 40,000 new recruits), unemployment rate was mediocre, and the relative pay favored the civilian sector. The other three runs also showed similar

trends where high accession missions, with a low number of recruiters in the field, and relative pay highly favoring the civilian sector resulted in unusually high expected recruiting costs. Identifying these costly outliers can help N1 analysts make informed recommendations to avoid situations like the 80th run by preemptively increasing the number of recruiters in the field.

To gain additional situational awareness of the data, the distributions and descriptive statistics for each decision variable are explored. Figure 60 shows the histogram of the distribution for total cost of recruiting over one FY of the PROM-WED excursion. Histogram and descriptive statistics for resourcing to advertisements and enlistment bonuses can be found in Appendix F.

Figure 60. Histogram and Descriptive Statistics for Total Cost of Recruiting Distribution for FY 2017

Total Cost of Recruiting



Quantiles

100.0%	maximum	974.1696
99.5%		974.1696
97.5%		875.44575
90.0%		533.85
75.0%	quartile	433.12145
50.0%	median	361.2135
25.0%	quartile	320.18825
10.0%		293.5959
2.5%		276.82095
0.5%		261.6095
0.0%	minimum	261.6095

Summary Statistics

Mean	398.24689
Std Dev	124.63855
Std Err Mean	10.973812
Upper 95% Mean	419.96045
Lower 95% Mean	376.53333
N	129

The histogram indicates that the distribution is highly skewed to the right. As well, the four data points that appear in the far right side of the histogram again represent runs 78, 80, 88, and 96.

Partition trees were used to understand how variable interactions and economic uncertainties affected the solution space. The partition trees in Figures 61 and 62 take into consideration the influence of each decision variable on the total cost of recruiting. Figure 61 shows the first split of the partition tree for total cost of recruiting, specifically for FY 2017.

Figure 61. First Split of Total Cost of Recruiting Partition Tree

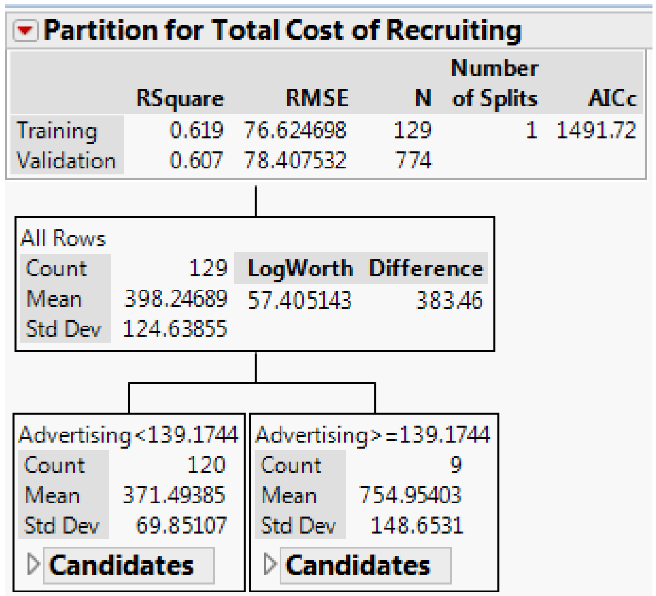
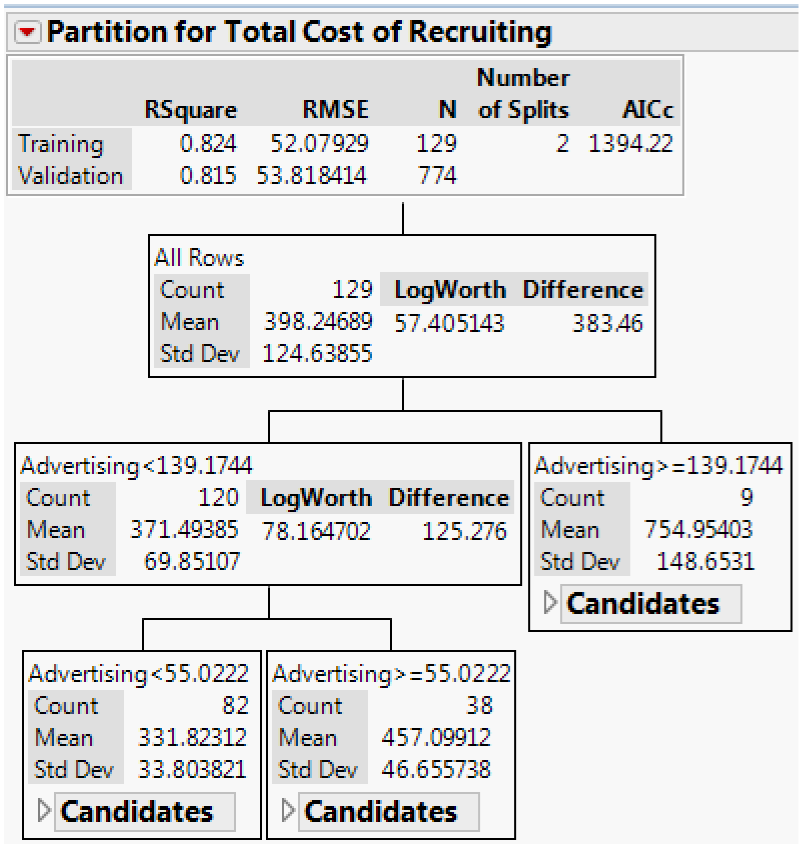


Figure 61 indicates that resourcing to advertising is the most influential predictor of the total cost of recruiting. 61.9 percent of the variance for the total cost of recruiting can be explained based on the first split of the partition tree. When less than $139 million is allocated to advertising, then the mean total cost of recruiting will be approximately $371 million. If more than $139 million is allocated to advertising, then the mean total cost of recruiting will increase to almost $755 million.

Figure 62 shows the next split of the partition tree shown in Figure 61.

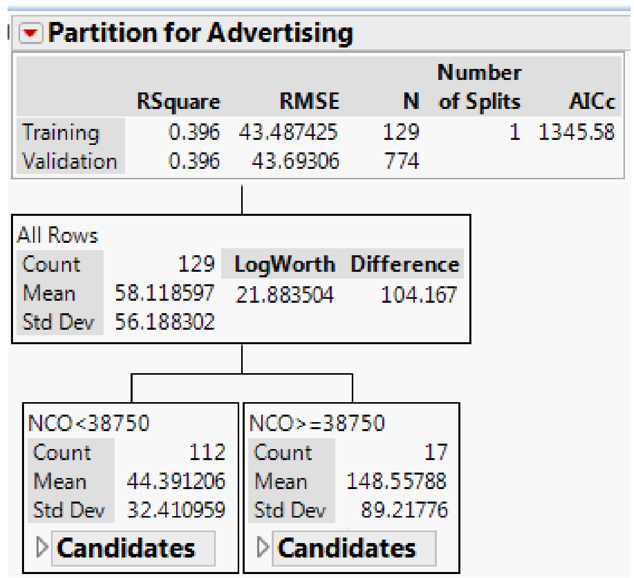
Figure 62. Second Split of Total Cost of Recruiting Partition Tree



The second split of the partition tree indicates that resourcing to advertising is identified again as the dominant predictor of the total cost of recruiting. Based on this split, over 80 percent of variance in the total cost of recruiting is explained. Repeated splitting of the same factor, in this case resources allocated to advertising, indicates regression may be a more informative analysis technique.

Next, a partition tree is used to understand which market factors most influence advertising. Figure 63 shows the parent and first child node of the partition tree for advertising.

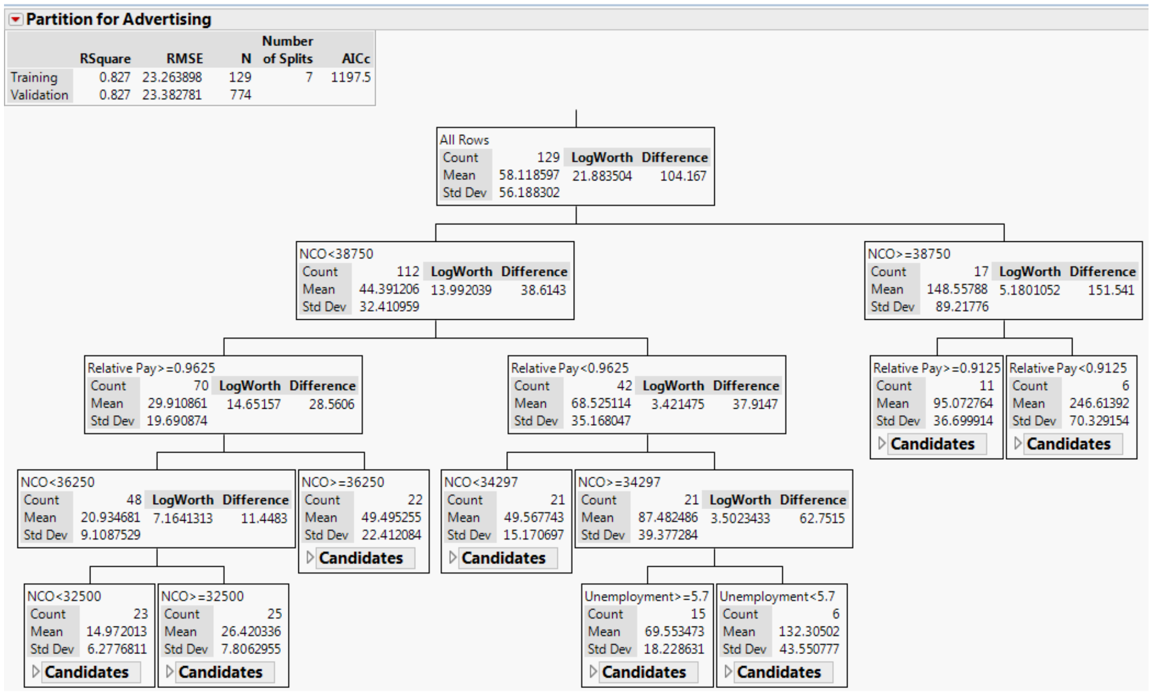
Figure 63. Parent and First Child Node of Partition Tree for Advertising



The partition tree in Figure 63 indicates that the recruiting accession mission is the most influential factor on the cost of advertising. The relatively small R-squared value indicates that a single split on accession mission explains only 39.6 percent of variance. In particular, if the accession mission is below 38,750 new recruits, the mean resourcing towards advertising is approximately $44.4 million. If the accession mission exceeds 38,750 new recruits, then the mean resourcing to advertising increases by over $100 million, to $148.6 million.

Following seven additional splits, as shown in Figure 64, it is evident that the resourcing of funds to advertising is influenced by many factors, to include: the new accession mission, relative pay, and to a small extent, the unemployment rate. Since it took seven splits to surpass the 80 percent R-squared threshold, it is evident that these three factors influence the resourcing of funds to advertising, but none of them particularly dominate.

Figure 64. Partition Tree for Advertising After Seven Splits



Stepwise regression is another method used to gain insights into how variables influence the solution space. Using stepwise regression with some manual judgement, the parameter estimates shown in Figure 65 are used to formulate the prediction model for the total cost of recruiting, shown in Figure 66.

Figure 65. Stepwise Regression for Total Cost of Recruiting

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	150.98005	70.71931	2.13	0.0348*
NCO	0.025536	0.001535	16.64	<.0001*
Unemployment	-24.59368	3.836157	-6.41	<.0001*
Relative Pay	-550.348	38.3648	-14.35	<.0001*
(NCO-35000.1)*(Relative Pay-1)	-0.127001	0.015311	-8.29	<.0001*
(NCO-35000.1)*(NCO-35000.1)	3.0499e-6	6.205e-7	4.92	<.0001*
(Relative Pay-1)*(Relative Pay-1)	1882.3763	384.6306	4.89	<.0001*

The stepwise regression model exhibits how the NOLH DOE allows for non-linear relationships and interactions.

Figure 66. Test Case 1, Prediction model for Total Cost of Recruiting

Prediction Expression

150.980052850998

+ 0.02553596931337 * NCO

+ -24.593679044673 * Unemployment

+ -550.34801858165 * Relative Pay

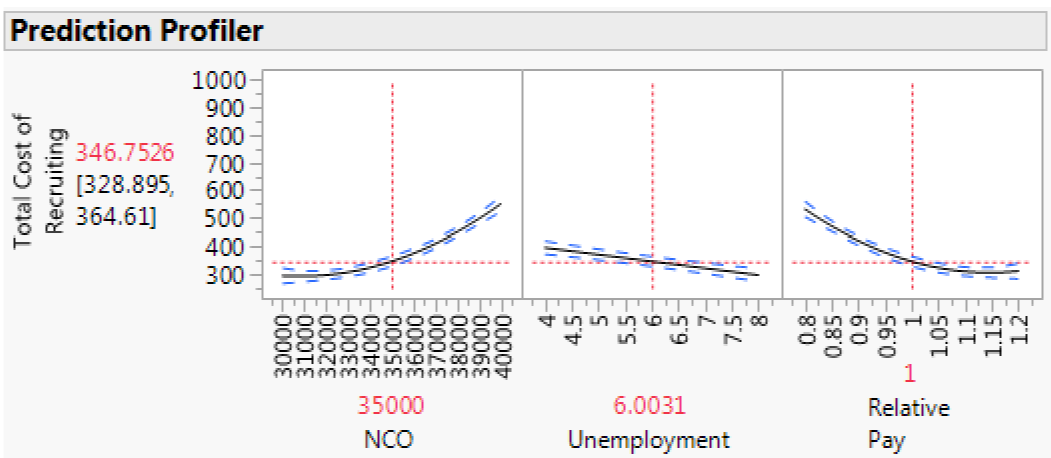
$$+ \left(\text{NCO} - 35000.0620155039\right) * \left(\left(\text{Relative Pay} - 1\right) * -0.1270005027034\right)$$

$$+ \left(\text{NCO} - 35000.0620155039\right) * \left(\left(\text{NCO} - 35000.0620155039\right) * 0.00000304992539\right)$$

$$+ \left(\text{Relative Pay} - 1\right) * \left(\left(\text{Relative Pay} - 1\right) * 1882.37625427676\right)$$

The prediction model for total cost of recruiting indicates that the new accession mission and relative pay interact to effect the total cost of recruiting. The new accession mission and relative pay both exhibit a non-linear behavior as evidence by their polynomial to degree two interactions. This relationship can also be visualized in the prediction profiler shown in Figure 67.

Figure 67. Prediction Profiler for Varying Factors in Test Case 1



The prediction profiles for the new accession mission and relative pay shown in Figure 67 demonstrate their quadratic nature.

Next, the summary of fit for the regression model shown is shown in Figure 68.

Figure 68. Summary of Fit for Total Cost of Recruiting Prediction Model

Summary of Fit	
RSquare	0.842252
RSquare Adj	0.834494
Root Mean Square Error	50.70598
Mean of Response	398.2469
Observations (or Sum Wgts)	129

This model explains over 84 percent of the variance of the total cost of recruiting for FY 2017.

To visualize a comparison of this model to actual FY 2017 data, the actual versus predicted plot is shown in Figure 69.

Figure 69. Test Case1, Actual by Predicted Plot for Total Cost of Recruiting

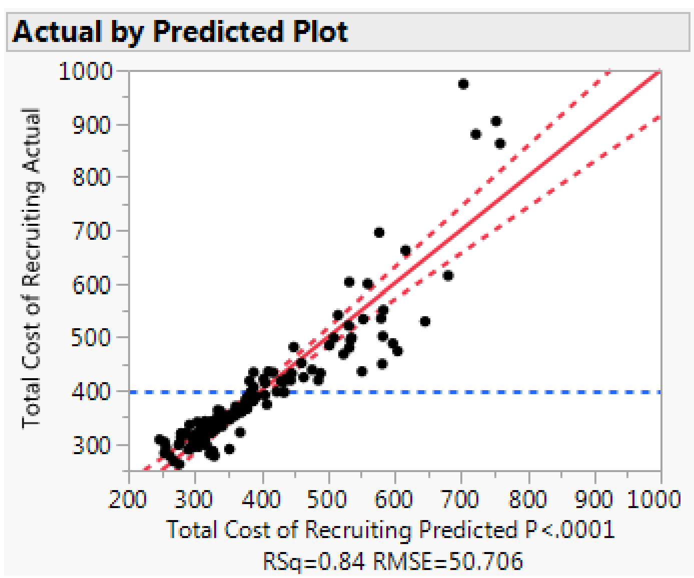
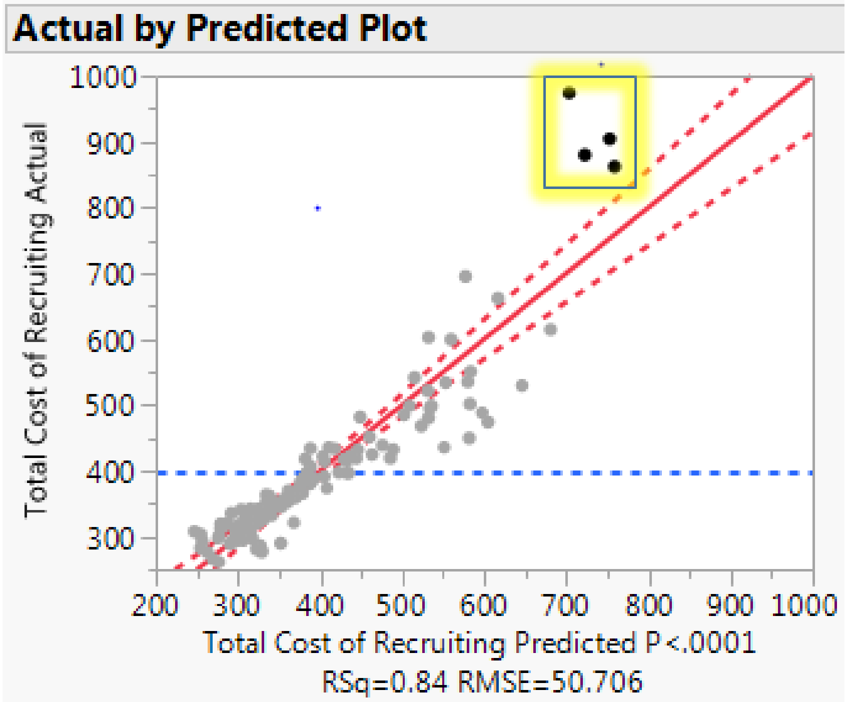


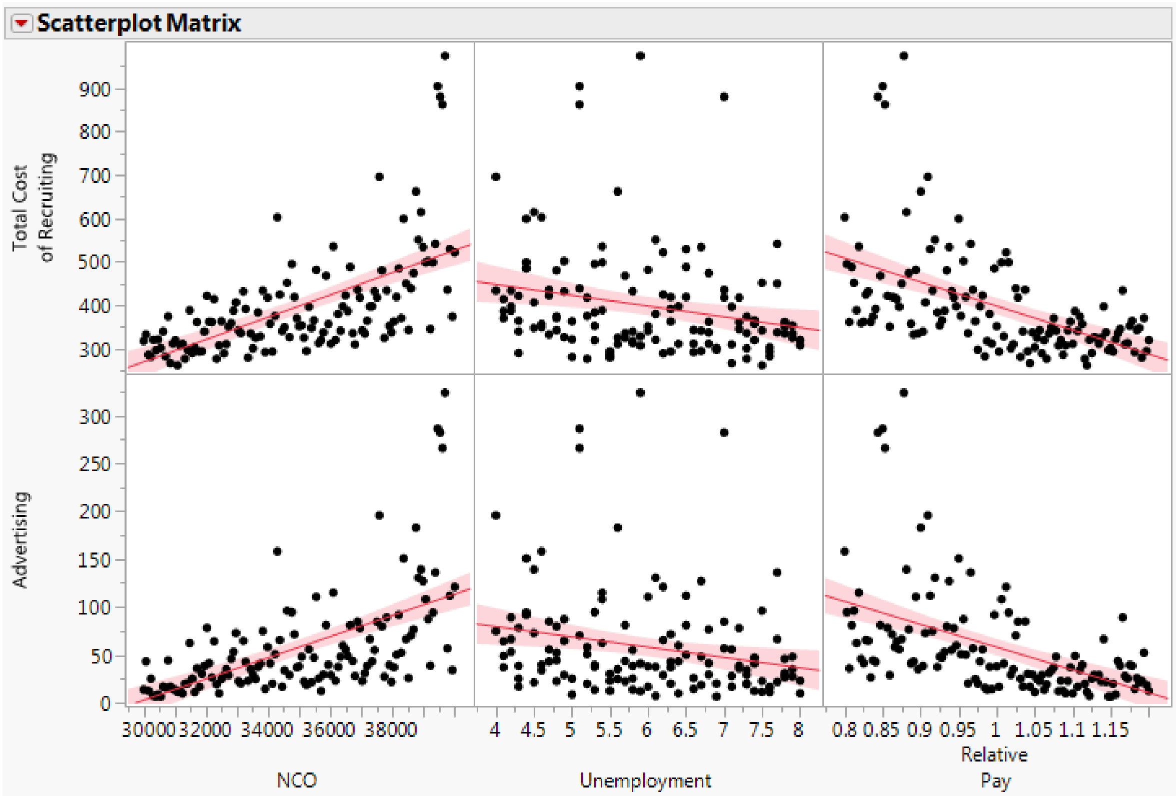
Figure 70 highlights the outlying points. Once again, runs 78, 80, 88 and 96 appear to be outliers.

Figure 70. Test Case1, Actual by Predicted Plot with Outliers



Since the new accession mission, unemployment rate, and relative pay drive advertising resourcing, six scatterplot matrices, shown in Figure 71, help analysts visualize trends amongst these factors against the total cost of recruiting and the resourcing of funds to advertising. As before, we plot the response (in this case, total cost of recruiting and advertising costs) against new accession mission, unemployment rate, and relative pay. The values for the new accession mission, unemployment rate, and relative pay come from the NOLH DOE. Other factors such as allocated funds to EB and the number of recruiters in the field, are also changing (EB is being optimized, while number of recruiters comes from the NOLH DOE). Therefore, the trends in these scatterplot matrices should be considered through the lens of a broad picture, not localized trends.

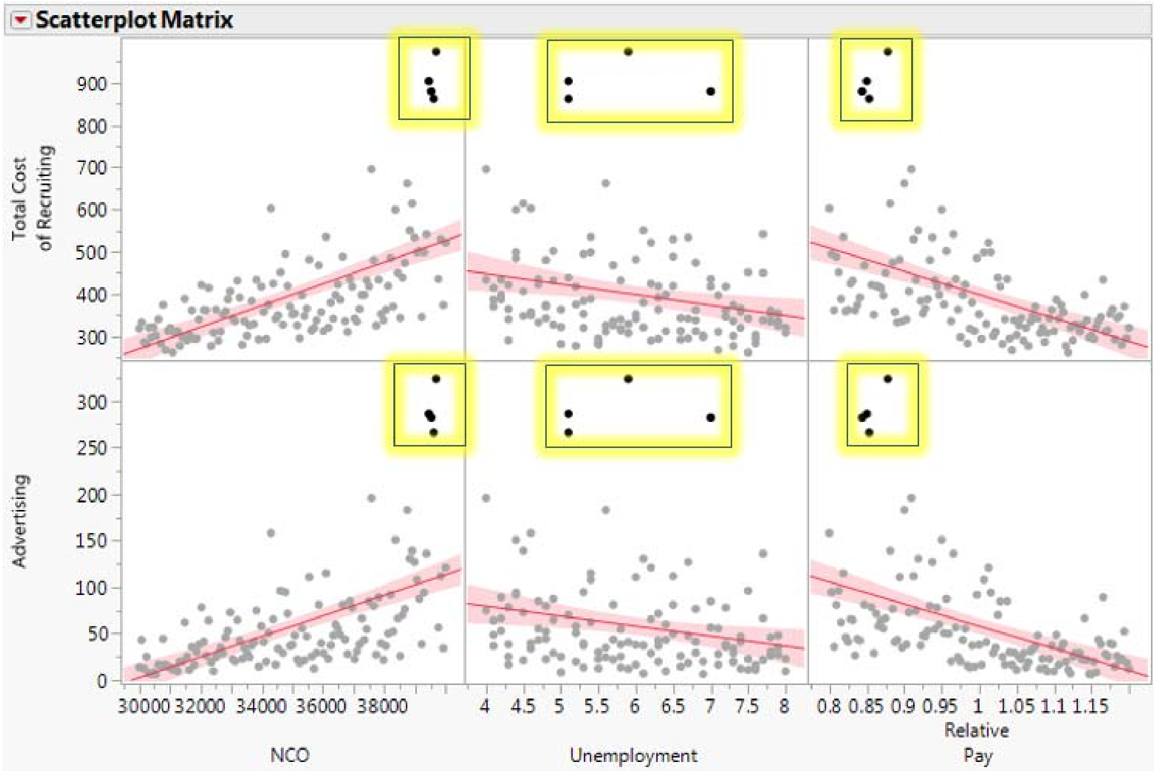
Figure 71. Economic Factor Trends on Recruiting Resource Allocation



The two scatterplot matrices for NCO versus advertising and NCO versus total cost of recruiting both indicate an upward trend, where a higher accession mission correlates with more resources allocated toward advertising and a higher total cost of recruiting. Both of the unemployment rate graphs show minor signs of a downward trend indicating that the cost of recruiting and the allocation of resources to advertising decreases, as the unemployment rate increases. Lastly, the relative pay versus advertising and relative pay versus total cost of recruiting graphs also indicate a trend. As the relative pay begins to increase, meaning wages favor the military over the civilian sector, resourcing towards advertising begins to decrease and the total cost of recruiting also decreases.

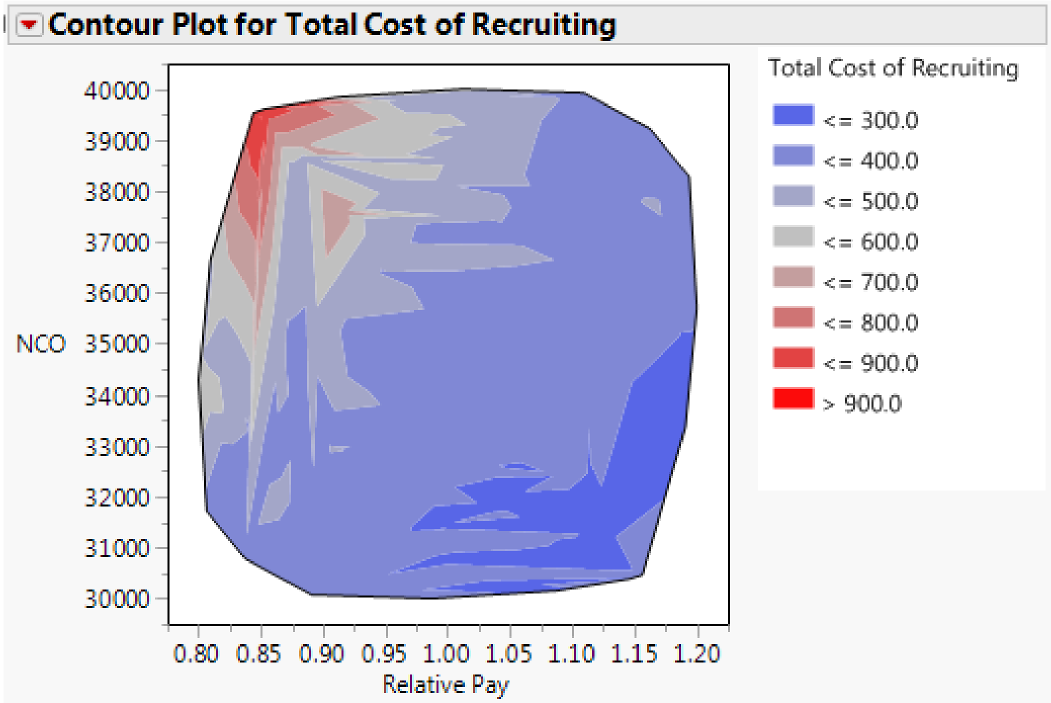
The four outlying points from runs 78, 80, 88 and 96 are present in these scatterplots as well. Figure 72 highlights results from these four runs. Once again, they appear to be outliers within each scatterplot.

Figure 72. Economic Factor Trends on Recruiting Resource Allocation with Outliers



Variable interactions can also be shown in a three-dimensional manner using contour plots. The contour plot in Figure 73 represents the interaction between relative pay and accession mission on the total cost of recruiting.

Figure 73. Three-Dimensional Representation of Relative Pay and NCO Effects on the Total Cost of Recruiting



The diagonal color transition indicates the presence of interactions. The red region, in the upper left portion of the plot represents the interaction between relative pay and new accession mission that result in the most costly conditions for Navy recruiting. This region represents when wages favor the civilian sector and the accession mission is high. The dark blue area represents the opposite conditions, where the total cost of recruiting is the lowest when the accession mission is relatively low and relative pay favors the military.

The contour plot shown in Figure 74 illustrates the relationship between relative pay and recruit accession mission on resources allocated toward advertising.

Figure 74. Three-Dimensional Representation of Relative Pay and NCO Effects Resourcing to Advertising

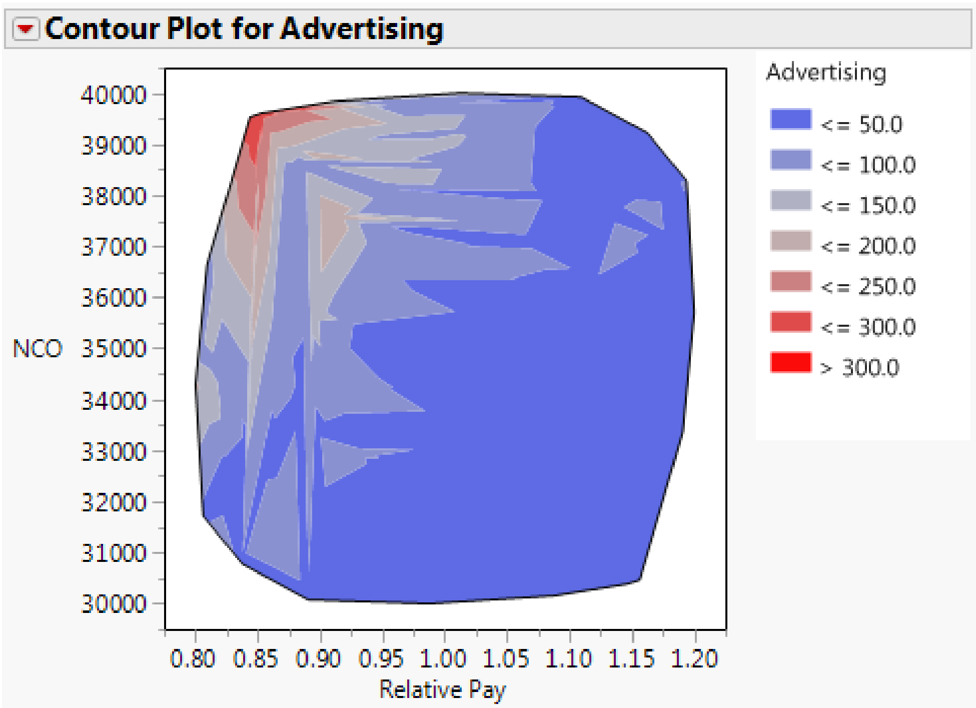


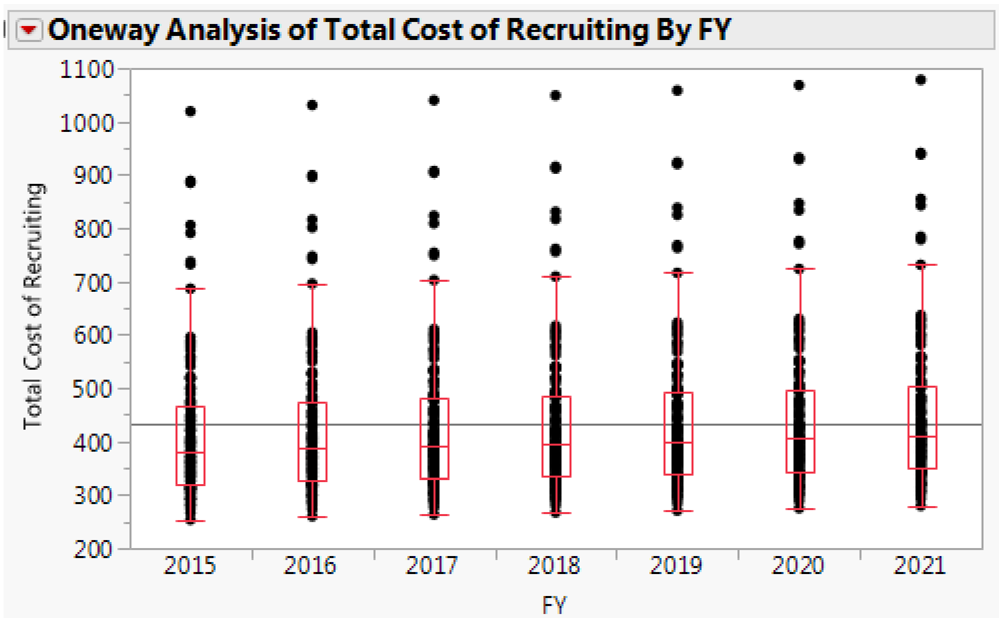
Figure 74, which also exhibits a diagonal nature, indicates that nearly half of the solution space supports a low advertising budget, represented by the dark blue region. The cost of advertising substantially increases when relative pay favors the civilian sector and the accession mission is high, represented by the red region. Once relative pay exceeds approximately 1.00, changes in the new accession mission have little to no effect on the amount of resources allocated to advertising.

2. Test Case 2

To further understand how the addition of two policy uncertainties affect the optimal allocation of recruiting resources, Test Case 2 is explored using JMP. As in the previous section, emphasis is placed on comparing insights gained that may distinguish Test Case 2 from Test Case 1.

To gain an initial understanding of the data, Figure 75 shows the span of possible costs of recruiting over each FY.

Figure 75. Total Cost of Recruiting by FY with Interquartile Ranges

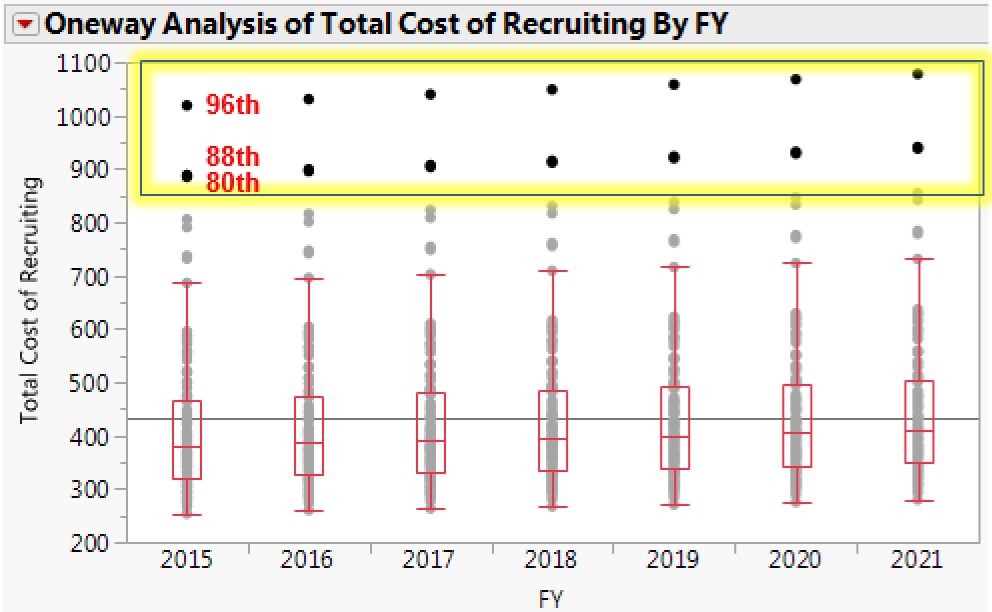


Quantiles

Level	Minimum	10%	25%	Median	75%	90%	Maximum
2015	253.7634	296.5226	318.9388	378.5047	467.3705	571.5925	1019.142
2016	260.1305	303.2767	325.8074	385.8551	475.3449	580.2986	1030.877
2017	263.6967	307.3261	329.9298	390.5322	480.6594	586.3599	1039.902
2018	267.3544	311.4732	334.3055	395.3136	486.0845	592.5386	1049.072
2019	271.0144	315.6291	338.7466	400.1104	491.531	598.7463	1058.296
2020	275.266	320.347	343.8861	405.5857	497.6674	605.6559	1068.192
2021	279.7699	325.1176	349.2917	411.3294	504.0784	612.8481	1078.395

It is evident that the grand mean total cost of recruiting increased by almost $50 million in comparison to Test Case 1’s grand mean total cost of recruiting shown previously in Figure 58. As well, Figure 76 shows that runs 80, 88, and 96 model conditions result in unusually high expected recruiting costs. From Figure 76, it is difficult to distinguish the difference between runs 80 and 88.

Figure 76. Test Case 2 Outliers



The input values that are common for each run over the seven FY excursion are shown in Table 15. The annual decrease in QMA values is explored later in this section.

Table 15. Test Case 2 Outlier Input Values

	Run #		
	80	88	96
Recruiters	2523	2727	2789
NCO	39688	39453	39609
UE	5.9	5.1	5.1
Relative Pay	0.878125	0.85	0.853125
TSC I-IIIA	0.83	0.71	0.85

In comparison to Test Case 1, where the 96th run was the "least extreme of the extreme" values, the 96th run for Test Case 2 consistently modeled the "most extreme of the extreme" values. This indicates that the increase in recruit quality and annual decrease in QMA affected the optimal allocation of recruiting resources.

Additional insights can be gained by comparing the quantile metrics for both Test Cases. The quantile charts for both test cases are shown in Figure 77.

Figure 77. Test Case 1 and Test Case 2 Quantile Charts

Quantiles

Level	Minimum	10%	25%	Median	75%	90%	Maximum
2015	251.8643	283.3929	309.1051	349.9401	421.2093	521.9235	959.1079
2016	258.138	289.8711	315.9455	356.89	428.4688	529.2777	968.0586
2017	261.6095	293.5959	320.1883	361.2135	433.1215	533.85	974.1696
2018	265.1709	297.4278	324.5511	365.861	437.8086	538.5172	980.3789
2019	268.7332	301.3375	329.0443	370.5412	442.3917	543.1901	986.5974
2020	272.8857	305.6795	334.2964	375.5285	447.5582	548.4681	993.3847
2021	277.2888	310.3785	339.8189	380.7692	453.0851	554.0022	1000.43

Quantiles

Level	Minimum	10%	25%	Median	75%	90%	Maximum
2015	253.7634	296.5226	318.9388	378.5047	467.3705	571.5925	1019.142
2016	260.1305	303.2767	325.8074	385.8551	475.3449	580.2986	1030.877
2017	263.6967	307.3261	329.9298	390.5322	480.6594	586.3599	1039.902
2018	267.3544	311.4732	334.3055	395.3136	486.0845	592.5386	1049.072
2019	271.0144	315.6291	338.7466	400.1104	491.531	598.7463	1058.296
2020	275.266	320.347	343.8861	405.5857	497.6674	605.6559	1068.192
2021	279.7699	325.1176	349.2917	411.3294	504.0784	612.8481	1078.395

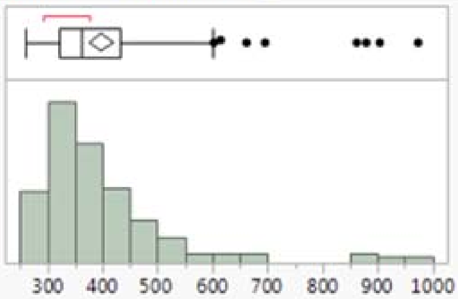
Top: Test Case 1; bottom: Test Case 2.

Figure 77 helps inform analysts that over each FY, Test Case 2 requires more resources than Test Case 1. The differences between the minimum values for each Test Case are approximately $2 million across each FY. This spread can increase upwards of $70 million when comparing differences between maximum values of both cases. As well, the interquartile ranges, the difference between the 25th and 75th quartiles which represent 50 percent of the data, is approximately $113 million for Test Case 1 and increases to approximately $150 million for Test Case 2.

Figure 78 juxtaposes the distributions and descriptive statistics for Test Case 1 and Test Case 2.

Figure 78. Distributions and Descriptive Statistics for Test Cases 1 and 2

Total Cost of Recruiting



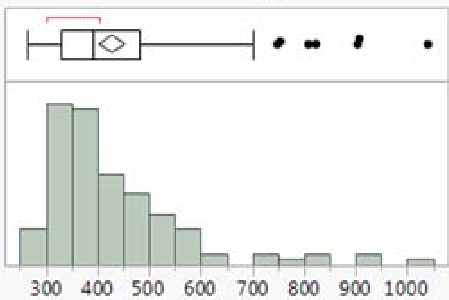
Quantiles

100.0%	maximum	974.1696
99.5%		974.1696
97.5%		875.44575
90.0%		533.85
75.0%	quartile	433.12145
50.0%	median	361.2135
25.0%	quartile	320.18825
10.0%		293.5959
2.5%		276.82095
0.5%		261.6095
0.0%	minimum	261.6095

Summary Statistics

Mean	398.24689
Std Dev	124.63855
Std Err Mean	10.973812
Upper 95% Mean	419.96045
Lower 95% Mean	376.53333
N	129

Total Cost of Recruiting



Quantiles

100.0%	maximum	1039.9023
99.5%		1039.9023
97.5%		883.5796
90.0%		586.3599
75.0%	quartile	480.6594
50.0%	median	390.5322
25.0%	quartile	329.9298
10.0%		307.3261
2.5%		286.1116
0.5%		263.6967
0.0%	minimum	263.6967

Summary Statistics

Mean	428.36779
Std Dev	135.96931
Std Err Mean	11.97143
Upper 95% Mean	452.05531
Lower 95% Mean	404.68027
N	129

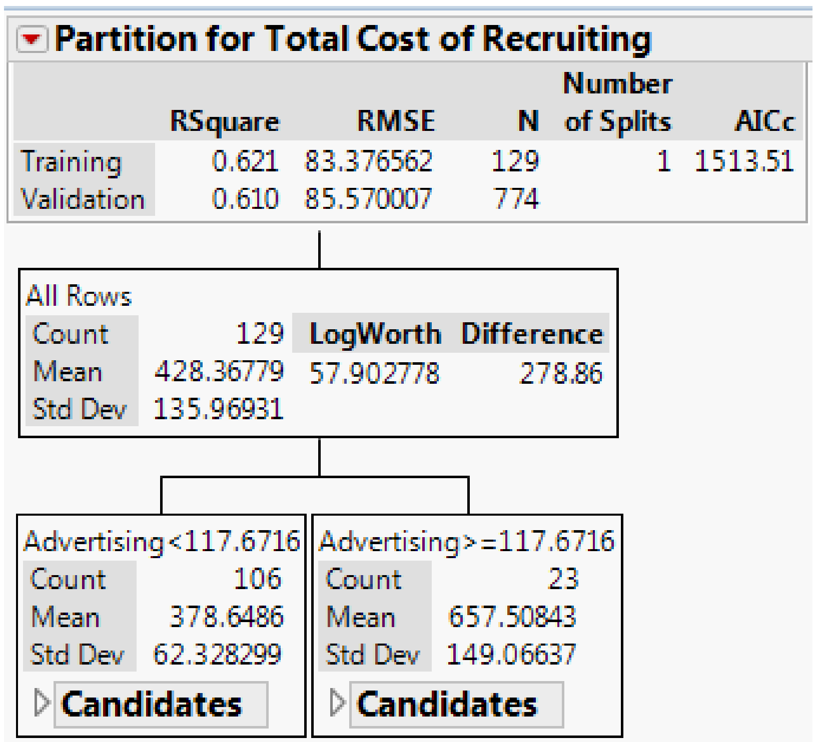
Top: Test Case 1; bottom: Test Case 2.

Figure 78 indicates that the distribution of recruiting costs for Test Case 2 is positively skewed with a long right tail, as was the case for Test Case 1. Test Case 2's right tail appears to be wider than what was seen for Test Case 1. A wider right tail indicates that Test Case 2 produced more expensive combinations of recruiting resources, also referred to as outliers, in comparison to Test Case 1.

When comparing the mean and median values for each Test Case, the differences between the mean and median values for Test Case 1 and Test Case 2 are approximately equal, at $37 million and $38 million, respectively. This suggests that the mean total cost of recruiting is heavily influenced by the outliers, but even with the presence of more outliers in Test Case 2, the differences between the mean and median estimators are negligible.

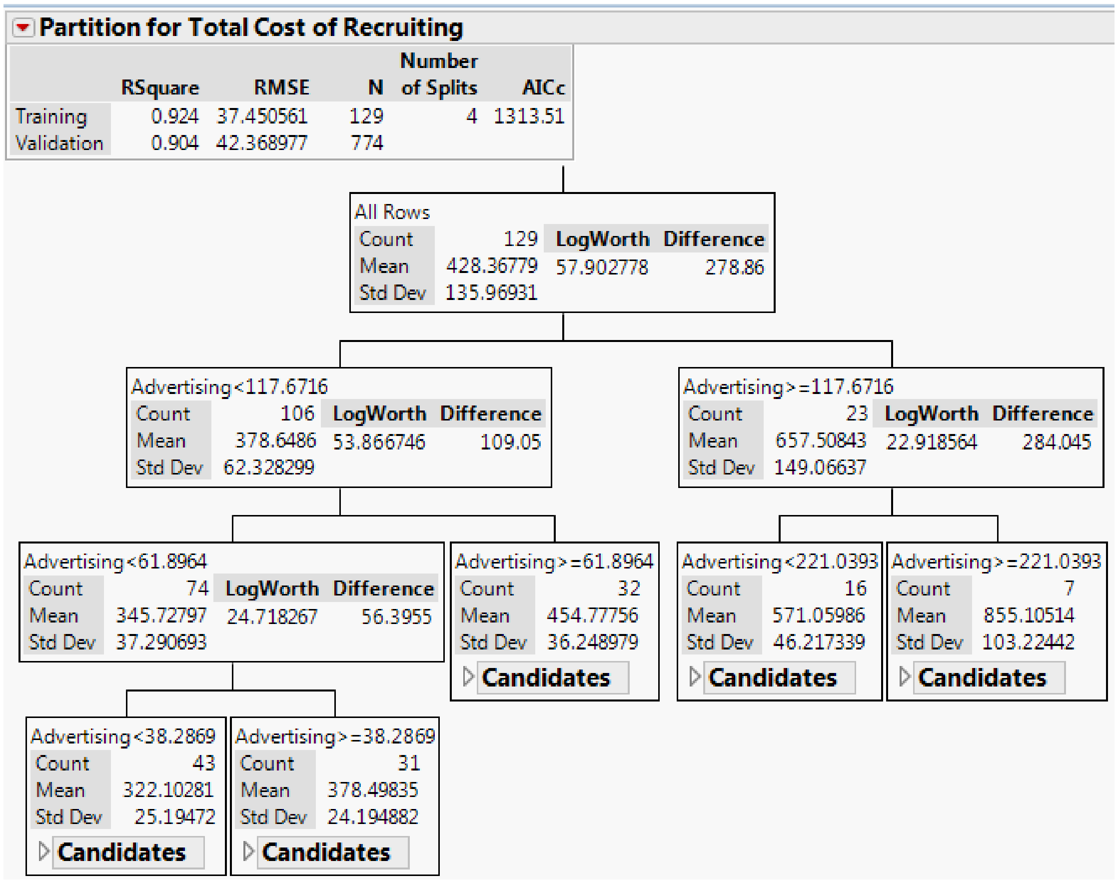
As in Test Case 1, a partition tree identifies advertising as the most influential decision variable for Test Case 2. Figure 79 shows that 62.1 percent of variance in the total cost of recruiting can be explained from a split on advertising.

Figure 79. First Split for Test Case 2



Following four splits, Figure 80 indicates that when the R-squared value exceeds .80, and even .92 in this case, advertising continues to dominate the partition tree.

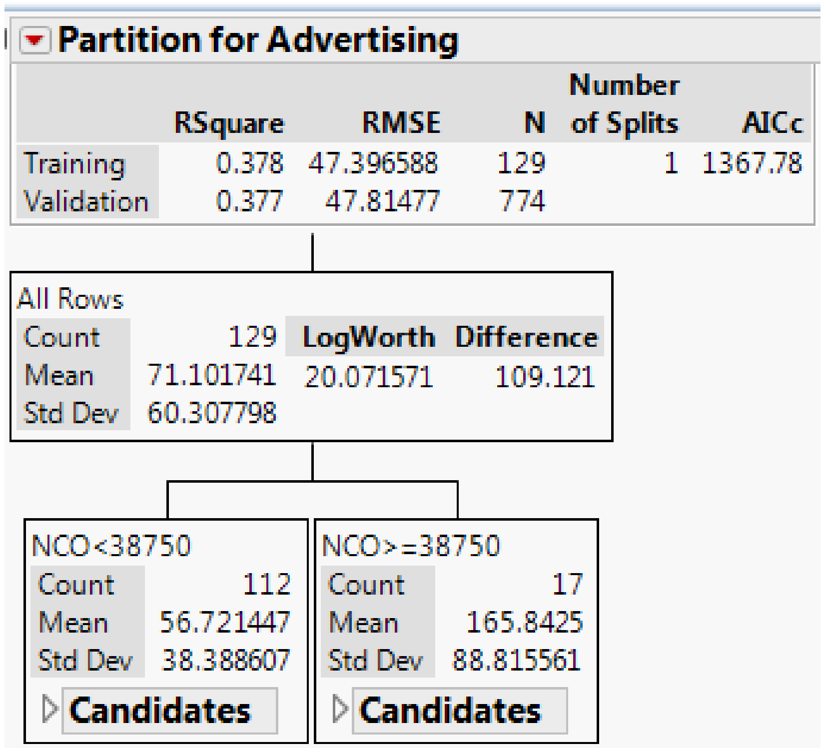
Figure 80. Test Case 2 Following Four Splits



As in Test Case 1, repeated splitting on advertising indicates regression as an appropriate technique for further analysis.

Partition trees are also constructed to determine how uncertainties in QMA and a policy change in recruit quality could affect resourcing to advertising. Here advertising is the response variable and we are investigating which factors influence advertising. Figure 81 shows the first split of this tree.

Figure 81. Test Case 2: First Split of Advertising



Similar to results found in Test Case 1, the new accession mission is identified as the dominant factor, but it maintains a low variance explained at 37.8 percent. Following three more splits, the R-squared value doubled. The resulting partition tree is shown in Figure 82.

Figure 82. Test Case 2: Partition Tree for Advertising

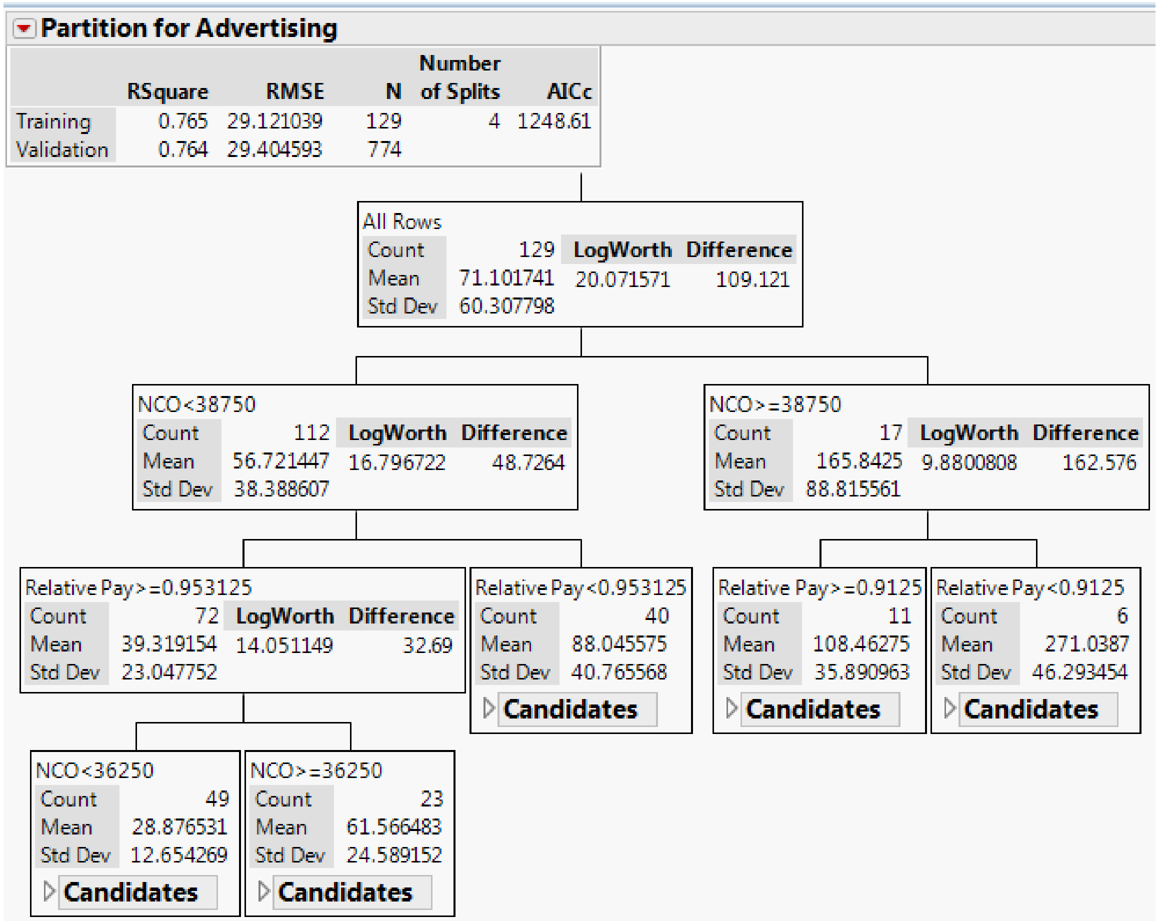


Figure 82 indicates that the new accession mission and relative pay predominately drive the allocation of resources to advertising. It is interesting to note that neither QMA nor recruit quality appear in this partition tree. This suggests that they have a minimal, if any, influence on advertising resources.

Again, stepwise regression with manual judgement, is used to formulate a model to predict the total cost of recruiting for Test Case 2. The parameter estimates used to formulate the prediction model are shown in Figure 83.

Figure 83. Test Case 2, Stepwise Regression for Total Cost of Recruiting

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-126.5045	74.71878	-1.69	0.0931
NCO	0.0266897	0.001086	24.57	<.0001*
TSC I-IIIA	562.69782	72.19942	7.79	<.0001*
Unemployment	-33.33182	2.715898	-12.27	<.0001*
Relative Pay	-662.512	27.15714	-24.40	<.0001*
(NCO-35000.1)*(Unemployment-6.0031)	-0.005165	0.001003	-5.15	<.0001*
(NCO-35000.1)*(Relative Pay-1)	-0.120308	0.010921	-11.02	<.0001*
(TSC I-IIIA-0.77504)*(Relative Pay-1)	-2866.773	673.4763	-4.26	<.0001*
(Unemployment-6.0031)*(Relative Pay-1)	135.38315	24.1139	5.61	<.0001*
(NCO-35000.1)*(NCO-35000.1)	2.3921e-6	4.485e-7	5.33	<.0001*
(Relative Pay-1)*(Relative Pay-1)	1980.2703	278.714	7.11	<.0001*

The parameter estimates shown in Figure 83, formulate the prediction model shown in Figure 84.

Figure 84. Test Case 2, Prediction model for Total Cost of Recruiting

Prediction Expression

-126.5044997643

+ 0.02668971455148 * NCO

+ 562.697816223402 * TSC I-IIIA

+ -33.3318158052 * Unemployment

+ -662.51203008942 * Relative Pay

+ (NCO - 35000.0620155039) * ((Unemployment - 6.0031007751938) * -0.0051646636056)

+ (NCO - 35000.0620155039) * ((Relative Pay - 1) * -0.1203081976383)

+ (TSC I-IIIA - 0.77503875968992) * ((Relative Pay - 1) * -2866.7729142712)

+ (Unemployment - 6.0031007751938) * ((Relative Pay - 1) * 135.383146993767)

+ (NCO - 35000.0620155039) * ((NCO - 35000.0620155039) * 0.00000239213948)

+ (Relative Pay - 1) * ((Relative Pay - 1) * 1980.27034394266)

As in Test Case 1, this prediction model indicates the presence of variable interactions and non-linear effects. Test Case 2 appears to be highly influenced by multi-variable interactions. Where Test Case 1 had just one multi-variable interaction and two quadratic terms, Test Case 2's prediction model has four multi-variable interactions and two quadratic terms. The regression model shown in Figure 84 provides evidence to believe that the addition of these two policy uncertainties (i.e., percentage of high quality recruits and decrease in QMA) does increase the complexity of recruiting resource allocation and effects the total cost of recruiting.

The summary of fit for Test Case 2's prediction model is shown in Figure 85.

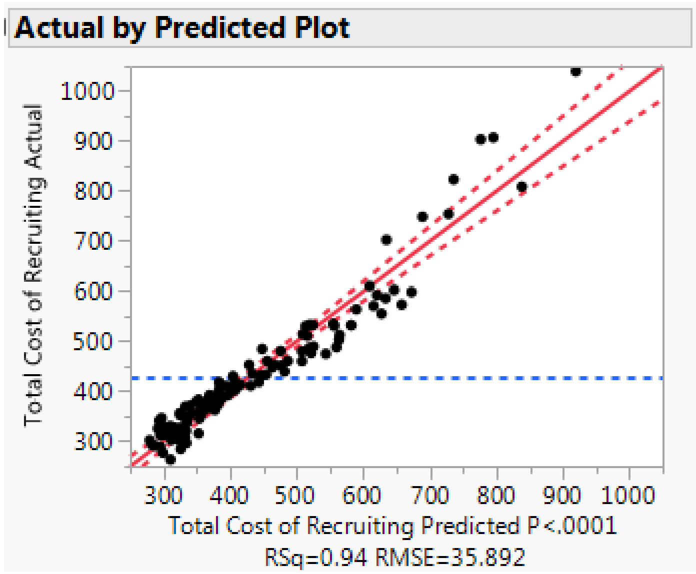
Figure 85. Summary of Fit for Test Case 2's Prediction Model for Total Cost of Recruiting

Summary of Fit	
RSquare	0.935761
RSquare Adj	0.930318
Root Mean Square Error	35.89242
Mean of Response	428.3678
Observations (or Sum Wgts)	129

This prediction model explains over 93 percent of the variance in the total cost of recruiting.

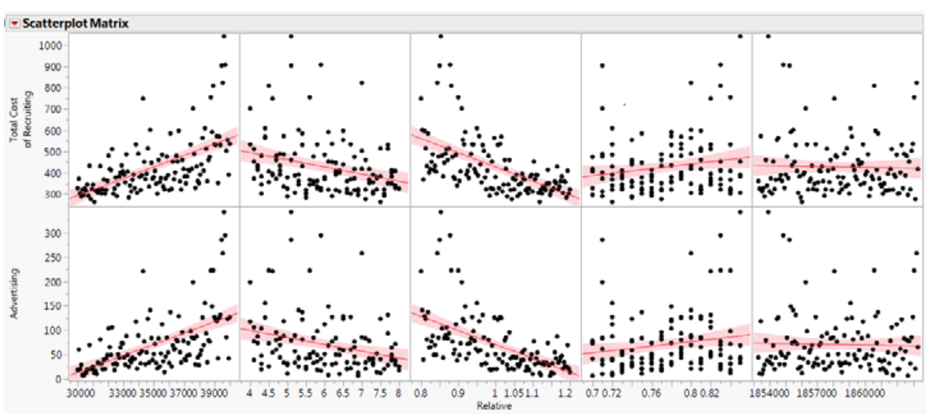
The actual versus predicted plot in Figure 86 illustrates how the prediction model compares to the actual data for FY 2017.

Figure 86. Test Case 2, Actual versus Predicted Plot



The factors that were determined to be influential through the partition tree and stepwise regression are fit in scatterplot matrices to visualize trends or relationships of the data, as shown in Figure 87. QMA was also included for comparison even though it is not considered an influential factor.

Figure 87. Test Case 2: Scatterplot Matrices of Influential Factors



As in Test Case 1, relative pay and NCO follow similar trends. Both scatterplot graphs for the percentage of high quality recruits show a slightly

upward linear trend. This indicates that an increased percentage of high quality recruits requires more resourcing to advertising, thus resulting in high overall recruiting costs. Both unemployment rate graphs show a slight downward trend, indicating that the total cost of recruiting and the total cost of advertising decreases as the unemployment rate increases. The recruit quality scatterplots suggest that as the requirement for recruit quality increases, more funds need to be allocated to advertising and the total cost of recruiting increases. Both scatterplots for QMA do not indicate any discernible trends.

D. FULL FACTORIAL COMPARISON

The NOLH DOE technique is the foundation for PROM-WED's data farming wrapper. Coupled with PROM-WED's GUI, users are able to design, populate, and execute space-filling experimental designs quickly and easily. Without the NOLH DOE, PROM-WED's data farming wrapper would not be as effective.

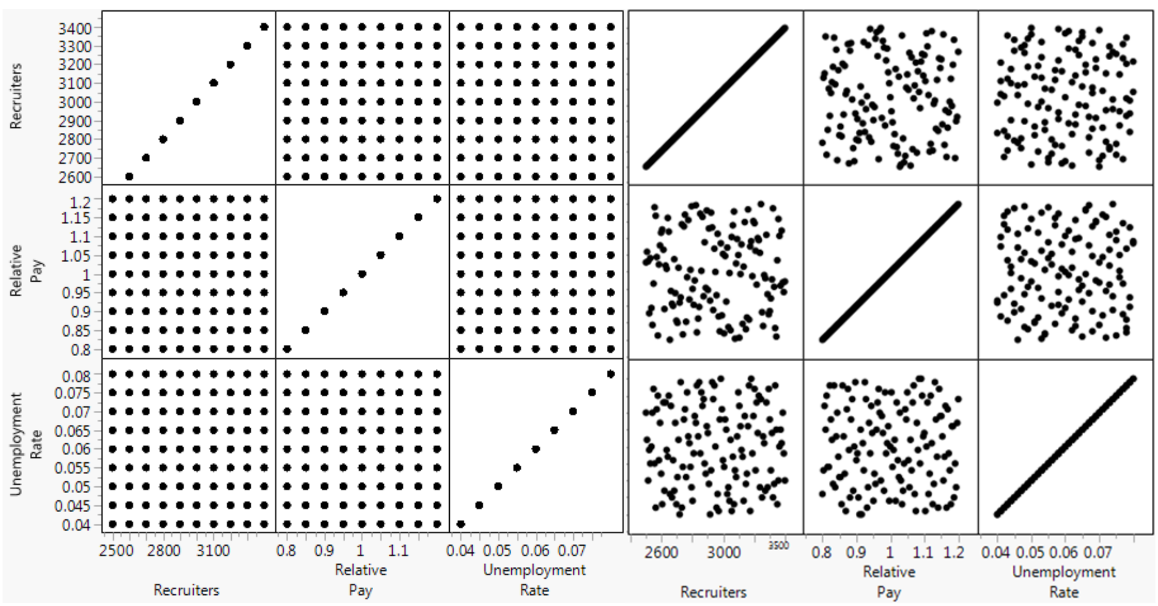
As previously described in Chapter II, the NOLH DOE method is an alternative to the straightforward full factorial method. A modified version of Test Case 1 is used to demonstrate what a potential full factorial could look like. This design tests three variables at only nine levels each. Table 16 shows an illustrative example of what nine levels for each variable could look like.

Table 16. Full Factorial Levels for Modified Test Case 1

Levels	Relative Pay	Unemployment Rate	Recruiters
1	0.80	4.0%	30,000
2	0.85	4.5%	31,000
3	0.90	5.0%	32,000
4	0.95	5.5%	33,000
5	1.00	6.0%	34,000
6	1.05	6.5%	35,000
7	1.10	7.0%	36,000
8	1.15	7.5%	37,000
9	1.20	8.0%	38,000

In comparison to the NOLH DOE, where each variable is tested at either 33 or 129 levels, for this full factorial example each variable is tested over only nine levels. To test all possible variable interactions the full factorial DOE would have to be run over 729 input combinations for each FY. 729 runs for each FY results in 5,103 runs for all seven FY's. This is in comparison to 231 runs for the 33-point NOLH design, or 903 runs for the 129-point NOLH design, which account for all runs over all seven FYs. The pairwise scatterplot matrices of a multi-level full factorial design in comparison to the 129 design point NOLH are shown in Figure 88.

Figure 88. Pairwise Plots of Full Factorial versus NOLH 129 Point Designs



Left: Full Factorial. Right: 128-point NOLH DOE.

As is evident by these pairwise plots, the NOLH DOE is able to execute space-filling designs with a fraction of runs.

Not only is the NOLH DOE method an efficient and effective alternative to the factorial DOE method, PROM-WED demonstrates that the NOLH DOE can be embedded into a model to add a robust data farming capability. The NOLH

DOE algorithm built in Microsoft Excel by the SEED Center for Data Farming at NPS provides this capability. Statistical software packages, like JMP, have a factorial DOE capability. However, to use this method an analyst would have to build the factorial DOE in JMP and import the design into Microsoft Excel. Embedding the NOLH DOE within the legacy PRO model alleviates this extra step, while also providing analysts with enhanced analytic abilities through efficient and effective space-filling designs that provide opportunities for robust sensitivity and risk analysis.

E. DISCUSSION

PROM-WED is an enhanced analytic tool capable of providing PRO model users with insights to better inform recruiting resource allocation decisions. The legacy PRO model produces a point-solution output, as shown in Figure 89.

Figure 89. Legacy PRO Model Output

Resource Run	2015	2016	2017	2018	2019	2020	2021
NCO	35,025	36,425	36,800	35,800	35,225	34,650	34,650
Capacity	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Unemployment (%)	4.0	4.0	4.0	4.0	4.0	4.0	4.0
Total Recruiters	3,913	3,685	3,685	3,685	3,685	3,685	3,685
Total Recruiter Cost ($M)	$320.488	$305.122	$309.699	$314.344	$319.059	$324.618	$330.274
Advertising ($M)	$102.921	$264.167	$261.119	$184.724	$142.227	$115.543	$113.903
Enlistment Bonus ($M)	$40.971	$36.580	$41.340	$40.650	$42.230	$42.060	$42.810
Education Incentives ($M)	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000	$0.000
LRP ($M)	$7.440	$11.220	$11.280	$11.380	$11.430	$11.460	$11.670
HSDG	95%	95%	95%	95%	95%	95%	95%
TSC I-IIIA	70%	70%	70%	70%	70%	70%	70%
Total Cost ($M)	$471.820	$617.089	$623.438	$551.098	$514.946	$493.681	$498.656

POM FY17 version of the PRO model.

As showcased in this chapter, PROM-WED provides users with the ablility to efficiently and effectively grow space-filling designs that produce data sets of 33 or 129 points in minutes. This means that 33 or 129 data points as shown in Figure 89 are produced by only one run of PROM-WED. PROM-WED not only grows data, it also facilitates basic statistical analysis and allows for further exploration using a statistical software package to better inform decision makers on the optimal allocation of hundreds of millions of dollars to advertisements, enlistment bonuses, and recommended number of Navy recruiters in the field.

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V. CONCLUSIONS AND RECOMMENDATIONS

Through design of experiment techniques, PROM-WED provides PRO model users with an enhanced analytic tool capable of producing valuable insights into the optimal allocation of recruiting resources. Based on the findings of this study, each research question presented in Chapter I is answered. Recommendations for further work are also presented.

A. RESEARCH QUESTION 1

How can design of experiment techniques better inform decision maker's determination of the optimal and robust combination of recruiting resources?

Efficient DOE techniques help better inform decision makers on the optimal allocation of recruiting resources through the efficient and effective implementation of space-filling designs. Embedding the PRO model into a data farming environment provides users with the ability to execute space-filling design of experiments. Through a single PROM-WED excursion, it is possible to test 33 or 129 legacy PRO model scenarios. Each excursion is able to test how uncertainties and variations in controllable and uncontrollable factors may affect the allocation of recruiting resources. In this study, Test Case 1 and Test Case 2 are proof-of-concept examples. As demonstrated through Test Case 1, the most expensive resource is the number of recruiters in the field. However, it is apparent that the total cost of recruiting is highly dependent upon the allocation of funds to advertising. In order from high to low influence: the new accession mission, relative pay, and unemployment rate drive the amount of resources allocated to advertising. As for the additional policy factors included in the legalization of marijuana scenario explored in Test Case 2, there is evidence to believe that increasing the percentage of high quality recruits has a greater effect on the total cost of recruiting than the decrease in QMA. These few examples show only a small spectrum of the vast amount of information that PROM-WED can provide. Therefore, by using DOE techniques, PROM-WED is able to grow

PRO model data in a systematic and controlled way. By controlling variable uncertainties and interactions, analysts are able to gain insights such as the ones just described. These insights help better inform decision makers on determining the optimal and robust allocation of recruiting resources.

B. RESEARCH QUESTION 2

How can efficient design of experiment techniques be incorporated into the PRO model for future, on-the-spot risk, and sensitivity analysis?

The PRO model is embedded into a data farming environment through the implementation of the Microsoft Excel NOLH DOE algorithm made available by the SEED Center for Data Farming. An enhanced GUI allows users to populate the NOLH DOE worksheet for each factor they would like to vary. The NOLH DOE algorithm automatically generates values for either 33 or 129 levels for each variable. Code is written to loop over each combination of 33 or 129 different scenarios. The result is a data set of 33 or 129 PRO model runs for each PROM-WED excursion. PROM-WED provides automatically generated analysis in Microsoft Excel for on-the-spot risk and sensitivity analysis. To take advantage of the space-filling qualities that the NOLH DOE provides, results from using the 129-point design can be explored using any available software package, like JMP.

C. RESEARCH QUESTION 3

Can an enhanced PRO model give decision-makers a robust solution for the optimal allocation of recruiting resources?

An enhanced PRO model allows analysts to understand how uncertainties and fluctuations in controllable and uncontrollable factors affect the allocation of recruiting resources. A robust solution can be interpreted through two lenses: (1) resiliency, or (2) gained insight. A robust solution for the optimal allocation of recruiting resources in terms of resiliency is one that is not overly affected by variations in uncontrollable factors, to include economic uncertainties such as

unemployment rates, or controllable factors, such as increasing the percentage of high quality recruits. Test Case 1 provides insights to decision makers regarding the optimal allocation of recruiting resources that is impervious to best case, worst case, and most likely economic conditions. For example, comparing the program of record and PROM-WED's allocation of recruiting resources for Test Case 1, there is evidence to believe that the pre-determined recruiting allocation budget was within the same range of spending as PROM-WED's solution.

An alternative approach to interpreting robustness is through assessing the value of information gained through the data. PROM-WED provides analysts with the capability to data farm the PRO model. Using data farming, PROM-WED grows PRO model data in an efficient and space-filling way. Improved understanding of the solution space can range from basic sensitivity and risk analysis of the decision variables presented in PROM-WED's automatically generated decision support capability, to gaining insights into how uncertainties in input factors affect the optimal allocation of recruiting resources using a software package like JMP. Valuable insights like these help analysts better inform decision-makers on how factors such as uncertain unemployment rates, a proposed policy change, or constrained resources can affect the optimal allocation of recruiting resources.

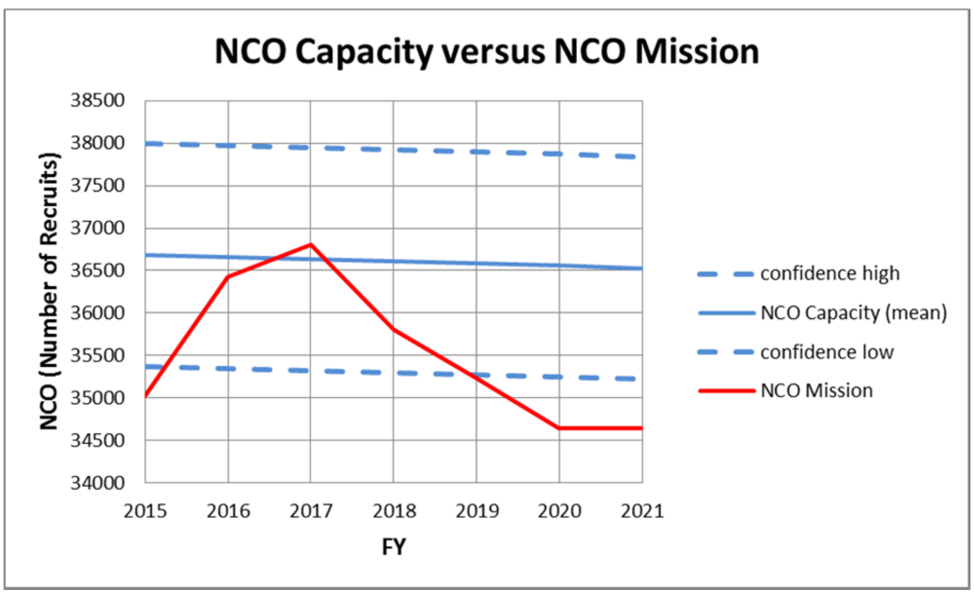
D. FUTURE WORK

The focus of this research was to enhance the existing PRO model with an efficient design of experiments capability. PROM-WED successfully data farms the PRO model's traditional run option. Recommendations for further work are separated into three sections. The first section addresses additional ways to improve PROM-WED. The second section addresses the opportunity to study and improve the PRO model's underlying mathematical construct. The last section addresses the opportunity to enhance any Microsoft Excel based model with techniques or methods employed in this research.

1. Capacity Run Capability and Additional Design Options

Further work is recommended to enhance PROM-WED with the addition of the capacity run option along with more design of experiment choices. While the capacity run option was briefly explored as a part of this research, additional work needs to be done to ensure that the data farming wrapper correctly enters input values in the appropriate locations within the PRO model's simulation worksheets, and extracts the correct output data. Once the data farming wrapper for the capacity run option is complete, its automatically generated decision support capability can be refined. Figure 90 shows a graph that a senior analyst at N1 requested to be included in the capacity run's automatically generated decision support analysis.

Figure 90. Example Capacity Run Graph



The new accession mission is shown in red and the expected capacity with a 95 percent confidence interval is shown in blue. This graph illustrates where the Navy has either budgeted an excess or deficient amount of resources to meet the recruiting mission. For example, in FYs 2020 and 2021, the Navy can

expect to recruit approximately 36,500 new recruits each year when only approximately 34,650 are needed. Since the NCO missions for FYs 2016, 2017, and 2018 are within the 95 percent confidence interval, there is evidence to believe that the pre-determined allocation of recruiting resources will be sufficient for those FYs.

Along with fully integrating the capacity run option into PROM-WED, work can be done to add other designs to PROM-WED's data farming wrapper. This will allow analysts to explore a broader realm of possibilities to gain additional insights about the complex solution space.

2. Recruiting Cost Function

For the purpose of this research, it was assumed that the PRO model accurately models active duty enlisted recruiting resource allocation. If this assumption were relaxed, the following additional research is suggested.

Within the "black box" of the recruiting cost function, elasticities can act as another variable with uncertainties. Currently, the elasticities are updated annually based on actual data from the previous FY. Therefore, further work can be done to include elasticities within PROM-WED's data farming wrapper. Also, future work can be done to explore the relevancy of the recruiting cost function in current recruiting practice.

The Navy is interested in incorporating the active duty officer, reserve officer, and reserve enlisted recruiting missions into the PRO model. This is a unique challenge since there are many diverse and unique communities within the active duty officer corps alone that require targeted recruiting initiatives. For example, Navy Doctors are often incentivized to join the Navy through a loan repayment program that alleviates medical school debt, or signing bonuses. On the other hand, loan repayment programs and signing bonuses are not available to prospective general line officers. Consequently, to recruit general line officers, large amounts of recruiting resources may be allocated to advertising in order to pay for college career fair booths.

Therefore, future work can be done to adapt the recruiting cost function to model the attributes of each unique recruiting mission. This additional work will provide analysts with an enhanced model that can help decision makers determine the optimal allocation of recruiting resources for the full spectrum of Navy recruiting.

3. Apply Data Farming to Another Model!

The methodology used to develop PROM-WED can be applied to any model built in Microsoft Excel. The NOLH DOE algorithms can be embedded into any Microsoft Excel model. Code similar to what is found in Appendix B can be written to loop over each design point of the NOLH. The resulting product is an enhanced tool that provides an efficient way to construct, run, and analyze a model using space-filling experimental designs.

APPENDIX A. 129-POINT NOLH DOE WORKSHEET

2	**low level**	**0.0001**	**0.04**	**3913**	**7.44**	**34.8264**	**40.971**	**35025**	**0.7**	**0.95**	**0.4**	**1883304**
3	**high level**	**0.0001**	**0.04**	**3913**	**7.44**	**34.8264**	**40.971**	**35025**	**0.7**	**0.95**	**0.4**	**1883304**
4	**decimals**	**4**	**2**	**0**	**3**	**3**	**3**	**0**	**2**	**2**	**6**	**0**
5	**ctor name**	**NCF + College First**	**Unemployment Rate**	**Recruiters**	**LRP**	**Advertising (AC Enl. Only)**	**EB**	**NCO (50% BoY DEP)**	**TSC I-IIIA**	**HSDG**	**Relative Pay**	**QMA**
6		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
7	2017	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
8		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
9		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
10		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
11		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
12		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
13		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
14		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
15		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
16		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
17		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
18		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
19		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
20		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
21		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
22		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
23		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
24		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
25		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
26		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
27		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
28		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
29		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
30		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
31		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
32		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
33		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
34		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
35		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
36		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
37		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
38		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
39		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
40		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
41		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
42		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
43		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
44		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
45		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
46		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
47		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
48		0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304

49	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
50	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
51	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
52	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
53	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
54	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
55	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
56	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
57	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
58	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
59	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
60	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
61	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
62	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
63	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
64	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
65	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
66	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
67	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
68	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
69	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
70	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
71	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
72	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
73	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
74	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
75	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
76	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
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82	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
83	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
84	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
85	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
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88	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
89	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
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91	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
92	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
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101	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
102	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
103	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
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106	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
107	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
108	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
109	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
110	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
111	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
112	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
113	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
114	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
115	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
116	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
117	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
118	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
119	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
120	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
121	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
122	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
123	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
124	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
125	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
126	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
127	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
128	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
129	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
130	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
131	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
132	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
133	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304
134	0.0001	0.04	3913	7.44	34.826	40.971	35025	0.7	0.95	0.4	1883304

APPENDIX B. DATA FARMING SUBROUTINE

```
Option Explicit
Sub NOLH33loop()
‘FY Loop

Dim wsNames As Variant
Dim wsCurrent As Variant
Dim I As Long
Dim j As Long

wsNames = Array(“Sheet6,” “Sheet10,” “Sheet11,” “Sheet12,” “Sheet13,”
“Sheet14,” “Sheet15”)

For Each wsCurrent In wsNames

‘With Worksheets(wsCurrent)
If wsCurrent = “Sheet6” Then Call NOLH33input15
If wsCurrent = “Sheet10” Then Call NOLH33input16
If wsCurrent = “Sheet11” Then Call NOLH33input17
If wsCurrent = “Sheet12” Then Call NOLH33input18
If wsCurrent = “Sheet13” Then Call NOLH33input19
If wsCurrent = “Sheet14” Then Call NOLH33input20
If wsCurrent = “Sheet15” Then Call NOLH33input21
Next wsCurrent

End Sub


Sub NOLH33input15()

Dim iterationNum As Long

‘Update Model year on Sim Tab
Sheet9.Range(“B3”) = Sheet6.Range(“A7”)

For iterationNum = 1 To 33

‘Ed Benefits
Sheet5.Range(“D17”) = Sheet6.Range(“B” & 4 + iterationNum)

‘UE Rates
Sheet9.Range(“C50”) = 100 * Sheet6.Range(“C” & 4 + iterationNum)
```

```
'Recruiters
Sheet5.Range("D19") = Sheet6.Range("D" & 4 + iterationNum)

'LRP
Sheet5.Range("D20") = Sheet6.Range("E" & 4 + iterationNum)

'Advertising
Sheet5.Range("D21") = Sheet6.Range("F" & 4 + iterationNum)

'EB
Sheet5.Range("D22") = Sheet6.Range("G" & 4 + iterationNum)

'NCO
Sheet9.Range("E11") = Sheet6.Range("H" & 4 + iterationNum)
'Sheet5.Range("D23") = Sheet6.Range("H" & 4 + iterationNum)
'Sheet5.Range("D12") = Sheet6.Range("H" & 4 + iterationNum)

'TSC I-IIIA
Sheet5.Range("N17") = Sheet6.Range("I" & 4 + iterationNum)

'HSDG
Sheet5.Range("N16") = Sheet6.Range("J" & 4 + iterationNum)

'Relative Pay
Sheet5.Range("D24") = Sheet6.Range("K" & 4 + iterationNum)

'QMA
Sheet5.Range("D25") = Sheet6.Range("L" & 4 + iterationNum)

' 'Update Model year on Sim Tab
' Sheet9.Range("B3") = Sheet6.Range("A7")

Call RunTraditional6

Sheet24.Range("B" & 1 + iterationNum) = Sheet3.Range("D3") 'NCO -> output
'Sheet24.Range("B" & 1 + iterationNum) = Sheet3.Range("D4") 'NCO cap ->
output
Sheet24.Range("C" & 1 + iterationNum) = Sheet3.Range("D5") 'Unemployment -
> output
Sheet24.Range("D" & 1 + iterationNum) = Sheet3.Range("D6") 'total recruiters ->
output
Sheet24.Range("E" & 1 + iterationNum) = Sheet3.Range("D7") 'total recruiters
cost to output
Sheet24.Range("F" & 1 + iterationNum) = Sheet3.Range("D8") 'advertising $ to
output
```

```
Sheet24.Range(“G” & 1 + iterationNum) = Sheet3.Range(“D9”) ‘EB $ to output
Sheet24.Range(“H” & 1 + iterationNum) = Sheet3.Range(“D10”) ‘ED $ to output
to output
Sheet24.Range(“I” & 1 + iterationNum) = Sheet6.Range(“E” & 4 + iterationNum)
‘wsResultsFY15.Range(“I” & 1 + designNumber) = pInputWorksheet.Cells(7, 20
+ iSimNumber) ‘LRP $ - a constant to output
Sheet24.Range(“J” & 1 + iterationNum) = Sheet3.Range(“D12”) ‘HSDG% to
output
Sheet24.Range(“K” & 1 + iterationNum) = Sheet3.Range(“D13”) ‘UMG% to
output
Sheet24.Range(“L” & 1 + iterationNum) = Sheet6.Range(“K” & 4 + iterationNum)
‘Relative Pay
Sheet24.Range(“M” & 1 + iterationNum) = Sheet6.Range(“L” & 4 + iterationNum)
‘QMA
Sheet24.Range(“N” & 1 + iterationNum) = Sheet6.Range(“A7”)

Next iterationNum

End Sub

Sub NOLH33input16()

Dim iterationNum As Long

‘Update Model year on Sim Tab
Sheet9.Range(“B3”) = Sheet10.Range(“A7”)

For iterationNum = 1 To 33

‘Ed Benefits
Sheet5.Range(“E17”) = Sheet10.Range(“B” & 4 + iterationNum)

‘UE Rates
Sheet9.Range(“C50”) = 100 * Sheet10.Range(“C” & 4 + iterationNum)

‘Recruiters
Sheet5.Range(“E19”) = Sheet10.Range(“D” & 4 + iterationNum)

‘LRP
Sheet5.Range(“D20”) = Sheet10.Range(“E” & 4 + iterationNum)

‘Advertising
Sheet5.Range(“E21”) = Sheet10.Range(“F” & 4 + iterationNum)

‘EB
```

```
Sheet5.Range(“E22”) = Sheet10.Range(“G” & 4 + iterationNum)

‘NCO
Sheet9.Range(“E11”) = Sheet10.Range(“H” & 4 + iterationNum)
‘Sheet5.Range(“D23”) = Sheet10.Range(“H” & 4 + iterationNum)

‘TSC I-IIIA
Sheet5.Range(“N17”) = Sheet10.Range(“I” & 4 + iterationNum)

‘HSDG
Sheet5.Range(“N16”) = Sheet10.Range(“J” & 4 + iterationNum)

‘Relative Pay
Sheet5.Range(“D24”) = Sheet10.Range(“K” & 4 + iterationNum)

‘QMA
Sheet5.Range(“D25”) = Sheet10.Range(“L” & 4 + iterationNum)

Call RunTraditional6

Sheet24.Range(“B” & 34 + iterationNum) = Sheet3.Range(“D3”) ‘NCO -> output
‘Sheet24.Range(“B” & 34 + iterationNum) = Sheet3.Range(“D4”) ‘NCO cap ->
output
Sheet24.Range(“C” & 34 + iterationNum) = Sheet3.Range(“D5”) ‘Unemployment
-> output
Sheet24.Range(“D” & 34 + iterationNum) = Sheet3.Range(“D6”) ‘total recruiters -
> output
Sheet24.Range(“E” & 34 + iterationNum) = Sheet3.Range(“D7”) ‘total recruiters
cost to output
Sheet24.Range(“F” & 34 + iterationNum) = Sheet3.Range(“D8”) ‘advertising $ to
output
Sheet24.Range(“G” & 34 + iterationNum) = Sheet3.Range(“D9”) ‘EB $ to output
Sheet24.Range(“H” & 34 + iterationNum) = Sheet3.Range(“D10”) ‘ED $ to output
to output
Sheet24.Range(“I” & 34 + iterationNum) = Sheet10.Range(“E” & 4 +
iterationNum)
‘wsResultsFY15.Range(“I” & 1 + designNumber) = pInputWorksheet.Cells(7, 20
+ iSimNumber) ‘LRP $ - a constant to output
Sheet24.Range(“J” & 34 + iterationNum) = Sheet3.Range(“D12”) ‘HSDG% to
output
Sheet24.Range(“K” & 34 + iterationNum) = Sheet3.Range(“D13”) ‘UMG% to
output
Sheet24.Range(“L” & 34 + iterationNum) = Sheet10.Range(“K” & 4 +
iterationNum) ‘Relative Pay
```

```
Sheet24.Range("M" & 34 + iterationNum) = Sheet10.Range("L" & 4 +
iterationNum) 'QMA
Sheet24.Range("N" & 34 + iterationNum) = Sheet10.Range("A7")

Next iterationNum

End Sub

Sub NOLH33input17()

Dim iterationNum As Long

'Update Model year on Sim Tab
Sheet9.Range("B3") = Sheet11.Range("A7")

For iterationNum = 1 To 33

'Ed Benefits
Sheet5.Range("F17") = Sheet11.Range("B" & 4 + iterationNum)

'UE Rates
Sheet9.Range("C50") = 100 * Sheet11.Range("C" & 4 + iterationNum)

'Recruiters
Sheet5.Range("F19") = Sheet11.Range("D" & 4 + iterationNum)

'LRP
Sheet5.Range("D20") = Sheet11.Range("E" & 4 + iterationNum)

'Advertising
Sheet5.Range("F21") = Sheet11.Range("F" & 4 + iterationNum)

'EB
Sheet5.Range("F22") = Sheet11.Range("G" & 4 + iterationNum)

'NCO
Sheet9.Range("E11") = Sheet11.Range("H" & 4 + iterationNum)
'Sheet5.Range("D23") = Sheet11.Range("H" & 4 + iterationNum)

'TSC I-IIIA
Sheet5.Range("N17") = Sheet11.Range("I" & 4 + iterationNum)

'HSDG
Sheet5.Range("N16") = Sheet11.Range("J" & 4 + iterationNum)
```

```
'Relative Pay
Sheet5.Range("D24") = Sheet11.Range("K" & 4 + iterationNum)

'QMA
Sheet5.Range("D25") = Sheet11.Range("L" & 4 + iterationNum)

Call RunTraditional6

Sheet24.Range("B" & 67 + iterationNum) = Sheet3.Range("D3") 'NCO -> output
Sheet24.Range("C" & 67 + iterationNum) = Sheet3.Range("D5") 'Unemployment
-> output
Sheet24.Range("D" & 67 + iterationNum) = Sheet3.Range("D6") 'total recruiters -
> output
Sheet24.Range("E" & 67 + iterationNum) = Sheet3.Range("D7") 'total recruiters
cost to output
Sheet24.Range("F" & 67 + iterationNum) = Sheet3.Range("D8") 'advertising $ to
output
Sheet24.Range("G" & 67 + iterationNum) = Sheet3.Range("D9") 'EB $ to output
Sheet24.Range("H" & 67 + iterationNum) = Sheet3.Range("D10") 'ED $ to output
to output
Sheet24.Range("I" & 67 + iterationNum) = Sheet11.Range("E" & 4 +
iterationNum)
'wsResultsFY15.Range("I" & 1 + designNumber) = pInputWorksheet.Cells(7, 20
+ iSimNumber) 'LRP $ - a constant to output
Sheet24.Range("J" & 67 + iterationNum) = Sheet3.Range("D12") 'HSDG% to
output
Sheet24.Range("K" & 67 + iterationNum) = Sheet3.Range("D13") 'UMG% to
output
Sheet24.Range("L" & 67 + iterationNum) = Sheet11.Range("K" & 4 +
iterationNum) 'Relative Pay
Sheet24.Range("M" & 67 + iterationNum) = Sheet11.Range("L" & 4 +
iterationNum) 'QMA
Sheet24.Range("N" & 67 + iterationNum) = Sheet11.Range("A7")

Next iterationNum

End Sub

Sub NOLH33input18()

Dim iterationNum As Long

'Update Model year on Sim Tab
Sheet9.Range("B3") = Sheet12.Range("A7")
```

```
For iterationNum = 1 To 33

‘Ed Benefits
Sheet5.Range(“G17”) = Sheet12.Range(“B” & 4 + iterationNum)

‘UE Rates
Sheet9.Range(“C50”) = 100 * Sheet12.Range(“C” & 4 + iterationNum)

‘Recruiters
Sheet5.Range(“G19”) = Sheet12.Range(“D” & 4 + iterationNum)

‘LRP
Sheet5.Range(“D20”) = Sheet12.Range(“E” & 4 + iterationNum)

‘Advertising
Sheet5.Range(“G21”) = Sheet12.Range(“F” & 4 + iterationNum)

‘EB
Sheet5.Range(“G22”) = Sheet12.Range(“G” & 4 + iterationNum)

‘NCO
Sheet9.Range(“E11”) = Sheet12.Range(“H” & 4 + iterationNum)
‘Sheet5.Range(“D23”) = Sheet12.Range(“H” & 4 + iterationNum)

‘TSC I-IIIA
Sheet5.Range(“N17”) = Sheet12.Range(“I” & 4 + iterationNum)

‘HSDG
Sheet5.Range(“N16”) = Sheet12.Range(“J” & 4 + iterationNum)

‘Relative Pay
Sheet5.Range(“D24”) = Sheet12.Range(“K” & 4 + iterationNum)

‘QMA
Sheet5.Range(“D25”) = Sheet12.Range(“L” & 4 + iterationNum)

Call RunTraditional6

Sheet24.Range(“B” & 100 + iterationNum) = Sheet3.Range(“D3”) ‘NCO -> output
Sheet24.Range(“C” & 100 + iterationNum) = Sheet3.Range(“D5”)
‘Unemployment -> output
Sheet24.Range(“D” & 100 + iterationNum) = Sheet3.Range(“D6”) ‘total recruiters
-> output
Sheet24.Range(“E” & 100 + iterationNum) = Sheet3.Range(“D7”) ‘total recruiters
cost to output
```

```
Sheet24.Range("F" & 100 + iterationNum) = Sheet3.Range("D8") 'advertising $
to output
Sheet24.Range("G" & 100 + iterationNum) = Sheet3.Range("D9") 'EB $ to output
Sheet24.Range("H" & 100 + iterationNum) = Sheet3.Range("D10") 'ED $ to
output to output
Sheet24.Range("I" & 100 + iterationNum) = Sheet12.Range("E" & 4 +
iterationNum)
'wsResultsFY15.Range("I" & 1 + designNumber) = pInputWorksheet.Cells(7, 20
+ iSimNumber) 'LRP $ - a constant to output
Sheet24.Range("J" & 100 + iterationNum) = Sheet3.Range("D12") 'HSDG% to
output
Sheet24.Range("K" & 100 + iterationNum) = Sheet3.Range("D13") 'UMG% to
output
Sheet24.Range("L" & 100 + iterationNum) = Sheet12.Range("K" & 4 +
iterationNum) 'Relative Pay
Sheet24.Range("M" & 100 + iterationNum) = Sheet12.Range("L" & 4 +
iterationNum) 'QMA
Sheet24.Range("N" & 100 + iterationNum) = Sheet12.Range("A7")

Next iterationNum

End Sub

Sub NOLH33input19()

Dim iterationNum As Long

'Update Model year on Sim Tab
Sheet9.Range("B3") = Sheet13.Range("A7")

For iterationNum = 1 To 33

'Ed Benefits
Sheet5.Range("H17") = Sheet13.Range("B" & 4 + iterationNum)

'UE Rates
Sheet9.Range("C50") = 100 * Sheet13.Range("C" & 4 + iterationNum)

'Recruiters
Sheet5.Range("H19") = Sheet13.Range("D" & 4 + iterationNum)

'LRP
Sheet5.Range("D20") = Sheet13.Range("E" & 4 + iterationNum)

'Advertising
```

```
Sheet5.Range("H21") = Sheet13.Range("F" & 4 + iterationNum)

'EB
Sheet5.Range("H22") = Sheet13.Range("G" & 4 + iterationNum)

'NCO
Sheet9.Range("E11") = Sheet13.Range("H" & 4 + iterationNum)
'Sheet5.Range("D23") = Sheet13.Range("H" & 4 + iterationNum)

'TSC I-IIIA
Sheet5.Range("N17") = Sheet13.Range("I" & 4 + iterationNum)

'HSDG
Sheet5.Range("N16") = Sheet13.Range("J" & 4 + iterationNum)

'Relative Pay
Sheet5.Range("D24") = Sheet13.Range("K" & 4 + iterationNum)

'QMA
Sheet5.Range("D25") = Sheet13.Range("L" & 4 + iterationNum)

Call RunTraditional6

Sheet24.Range("B" & 133 + iterationNum) = Sheet3.Range("D3") 'NCO -> output
Sheet24.Range("C" & 133 + iterationNum) = Sheet3.Range("D5")
'Unemployment -> output
Sheet24.Range("D" & 133 + iterationNum) = Sheet3.Range("D6") 'total recruiters
-> output
Sheet24.Range("E" & 133 + iterationNum) = Sheet3.Range("D7") 'total recruiters
cost to output
Sheet24.Range("F" & 133 + iterationNum) = Sheet3.Range("D8") 'advertising $
to output
Sheet24.Range("G" & 133 + iterationNum) = Sheet3.Range("D9") 'EB $ to output
Sheet24.Range("H" & 133 + iterationNum) = Sheet3.Range("D10") 'ED $ to
output to output
Sheet24.Range("I" & 133 + iterationNum) = Sheet13.Range("E" & 4 +
iterationNum)
'wsResultsFY15.Range("I" & 1 + designNumber) = pInputWorksheet.Cells(7, 20
+ iSimNumber) 'LRP $ - a constant to output
Sheet24.Range("J" & 133 + iterationNum) = Sheet3.Range("D12") 'HSDG% to
output
Sheet24.Range("K" & 133 + iterationNum) = Sheet3.Range("D13") 'UMG% to
output
Sheet24.Range("L" & 133 + iterationNum) = Sheet13.Range("K" & 4 +
iterationNum) 'Relative Pay
```

```
Sheet24.Range("M" & 133 + iterationNum) = Sheet13.Range("L" & 4 +
iterationNum) 'QMA
Sheet24.Range("N" & 133 + iterationNum) = Sheet13.Range("A7")

Next iterationNum

End Sub

Sub NOLH33input20()

Dim iterationNum As Long

'Update Model year on Sim Tab
Sheet9.Range("B3") = Sheet14.Range("A7")

For iterationNum = 1 To 33

'Ed Benefits
Sheet5.Range("I17") = Sheet14.Range("B" & 4 + iterationNum)

'UE Rates
Sheet9.Range("C50") = 100 * Sheet14.Range("C" & 4 + iterationNum)

'Recruiters
Sheet5.Range("I19") = Sheet14.Range("D" & 4 + iterationNum)

'LRP
Sheet5.Range("D20") = Sheet14.Range("E" & 4 + iterationNum)

'Advertising
Sheet5.Range("I21") = Sheet14.Range("F" & 4 + iterationNum)

'EB
Sheet5.Range("I22") = Sheet14.Range("G" & 4 + iterationNum)

'NCO
Sheet9.Range("E11") = Sheet14.Range("H" & 4 + iterationNum)
'Sheet5.Range("D23") = Sheet14.Range("H" & 4 + iterationNum)

'TSC I-IIIA
Sheet5.Range("N17") = Sheet14.Range("I" & 4 + iterationNum)

'HSDG
Sheet5.Range("N16") = Sheet14.Range("J" & 4 + iterationNum)
```

```
'Relative Pay
Sheet5.Range("D24") = Sheet14.Range("K" & 4 + iterationNum)

'QMA
Sheet5.Range("D25") = Sheet14.Range("L" & 4 + iterationNum)

Call RunTraditional6

Sheet24.Range("B" & 166 + iterationNum) = Sheet3.Range("D3") 'NCO -> output
Sheet24.Range("C" & 166 + iterationNum) = Sheet3.Range("D5")
'Unemployment -> output
Sheet24.Range("D" & 166 + iterationNum) = Sheet3.Range("D6") 'total recruiters
-> output
Sheet24.Range("E" & 166 + iterationNum) = Sheet3.Range("D7") 'total recruiters
cost to output
Sheet24.Range("F" & 166 + iterationNum) = Sheet3.Range("D8") 'advertising $
to output
Sheet24.Range("G" & 166 + iterationNum) = Sheet3.Range("D9") 'EB $ to output
Sheet24.Range("H" & 166 + iterationNum) = Sheet3.Range("D10") 'ED $ to
output to output
Sheet24.Range("I" & 166 + iterationNum) = Sheet14.Range("E" & 4 +
iterationNum)
'wsResultsFY15.Range("I" & 1 + designNumber) = pInputWorksheet.Cells(7, 20
+ iSimNumber) 'LRP $ - a constant to output
Sheet24.Range("J" & 166 + iterationNum) = Sheet3.Range("D12") 'HSDG% to
output
Sheet24.Range("K" & 166 + iterationNum) = Sheet3.Range("D13") 'UMG% to
output
Sheet24.Range("L" & 166 + iterationNum) = Sheet14.Range("K" & 4 +
iterationNum) 'Relative Pay
Sheet24.Range("M" & 166 + iterationNum) = Sheet14.Range("L" & 4 +
iterationNum) 'QMA
Sheet24.Range("N" & 166 + iterationNum) = Sheet14.Range("A7")

Next iterationNum

End Sub

Sub NOLH33input21()

Dim iterationNum As Long

'Update Model year on Sim Tab
Sheet9.Range("B3") = Sheet15.Range("A7")
```

```
For iterationNum = 1 To 33

'Ed Benefits
Sheet5.Range("J17") = Sheet15.Range("B" & 4 + iterationNum)

'UE Rates
Sheet9.Range("C50") = 100 * Sheet15.Range("C" & 4 + iterationNum)

'Recruiters
Sheet5.Range("J19") = Sheet15.Range("D" & 4 + iterationNum)

'LRP
Sheet5.Range("D20") = Sheet15.Range("E" & 4 + iterationNum)

'Advertising
Sheet5.Range("J21") = Sheet15.Range("F" & 4 + iterationNum)

'EB
Sheet5.Range("J22") = Sheet15.Range("G" & 4 + iterationNum)

'NCO
Sheet9.Range("E11") = Sheet15.Range("H" & 4 + iterationNum)
'Sheet5.Range("D23") = Sheet15.Range("H" & 4 + iterationNum)

'TSC I-IIIA
Sheet5.Range("N17") = Sheet15.Range("I" & 4 + iterationNum)

'HSDG
Sheet5.Range("N16") = Sheet15.Range("J" & 4 + iterationNum)

'Relative Pay
Sheet5.Range("D24") = Sheet15.Range("K" & 4 + iterationNum)

'QMA
Sheet5.Range("D25") = Sheet15.Range("L" & 4 + iterationNum)

Call RunTraditional6

Sheet24.Range("B" & 199 + iterationNum) = Sheet3.Range("D3") 'NCO -> output
Sheet24.Range("C" & 199 + iterationNum) = Sheet3.Range("D5")
'Unemployment -> output
Sheet24.Range("D" & 199 + iterationNum) = Sheet3.Range("D6") 'total recruiters
-> output
Sheet24.Range("E" & 199 + iterationNum) = Sheet3.Range("D7") 'total recruiters
cost to output
```

```
Sheet24.Range("F" & 199 + iterationNum) = Sheet3.Range("D8") 'advertising $
to output
Sheet24.Range("G" & 199 + iterationNum) = Sheet3.Range("D9") 'EB $ to output
Sheet24.Range("H" & 199 + iterationNum) = Sheet3.Range("D10") 'ED $ to
output to output
Sheet24.Range("I" & 199 + iterationNum) = Sheet15.Range("E" & 4 +
iterationNum)
'wsResultsFY15.Range("I" & 1 + designNumber) = pInputWorksheet.Cells(7, 20
+ iSimNumber) 'LRP $ - a constant to output
Sheet24.Range("J" & 199 + iterationNum) = Sheet3.Range("D12") 'HSDG% to
output
Sheet24.Range("K" & 199 + iterationNum) = Sheet3.Range("D13") 'UMG% to
output
Sheet24.Range("L" & 199 + iterationNum) = Sheet15.Range("K" & 4 +
iterationNum) 'Relative Pay
Sheet24.Range("M" & 199 + iterationNum) = Sheet15.Range("L" & 4 +
iterationNum) 'QMA
Sheet24.Range("N" & 199 + iterationNum) = Sheet15.Range("A7")

Next iterationNum

End Sub

Sub RunTraditional6()
Dim pCalcWorksheet As Worksheet
Dim pResultWorksheet As Worksheet
Dim pInputWorksheet As Worksheet
Dim pUserInterfaceWorksheet As Worksheet
Dim iSimNumber As Long
Dim iNumSimulations As Long
Dim iOldCalcalculationSetting As Long
Dim pUserWorksheet As Worksheet
Dim pTradRunsWorksheet As Worksheet
Dim casenum As Long
Dim designPoints As Long

Set pCalcWorksheet = ThisWorkbook.Worksheets("Simulation")
Set pResultWorksheet = ThisWorkbook.Worksheets("Output")
Set pInputWorksheet = ThisWorkbook.Worksheets("Input")
Set pUserInterfaceWorksheet = ThisWorkbook.Worksheets("User Interface")
Set pTradRunsWorksheet = ThisWorkbook.Worksheets("Traditional Runs")
iOldCalcalculationSetting = Application.Calculation
iNumSimulations = 7

Application.ScreenUpdating = False
```

```
Application.Calculation = xlCalculationManual
pResultWorksheet.Columns("B:Q").Clear
ThisWorkbook.Worksheets("Simulation").Activate
pCalcWorksheet.Cells(8, 2) = "User Defined"
'pCalcWorksheet.Cells(8, 2) = "Model Year"
pResultWorksheet.Cells(2, 3) = "Resource Run"
pCalcWorksheet.Cells(14, 2) = pUserInterfaceWorksheet.Cells(27, 4)
pCalcWorksheet.Cells(15, 2) = pUserInterfaceWorksheet.Cells(28, 4)
pCalcWorksheet.Cells(16, 2) = pUserInterfaceWorksheet.Cells(29, 4)
pCalcWorksheet.Cells(17, 2) = pUserInterfaceWorksheet.Cells(30, 4)

For casenum = 1 To 3 'Run through High UE, Base UE, Low UE scenarios
ThisWorkbook.Worksheets("User Interface").Activate
pUserInterfaceWorksheet.Cells(18, 17) = casenum
ThisWorkbook.Worksheets("Simulation").Activate


'Just for FY 2015
For iSimNumber = 1 To 1

'pCalcWorksheet.Cells(3, 2) = pCalcWorksheet.Cells(9 + iSimNumber, 29)
'Updates the model year
Application.Calculate 'Recalculates sheet
'pResultWorksheet.Cells(2, 3 + iSimNumber) = iSimNumber + 2014 'Copies
Model Year to output
pResultWorksheet.Cells(3, 3 + iSimNumber) = pCalcWorksheet.Cells(11, 5) '4
'Copies NCO to output
pResultWorksheet.Cells(4, 3 + iSimNumber) = "N/A" 'Copies Capacity to output
pResultWorksheet.Cells(5, 3 + iSimNumber) = pCalcWorksheet.Cells(50, 3)
'Copies unemployment to output
pResultWorksheet.Cells(6, 3 + iSimNumber) = pCalcWorksheet.Cells(8, 9)
'Copies total recruiters to output
pResultWorksheet.Cells(7, 3 + iSimNumber) = pCalcWorksheet.Cells(8, 10)
'Copies total recruiters cost to output
pResultWorksheet.Cells(8, 3 + iSimNumber) = pCalcWorksheet.Cells(9, 10)
'Copies advertising $ to output
pResultWorksheet.Cells(9, 3 + iSimNumber) = pCalcWorksheet.Cells(10, 10)
'Copies EB $ to output
pResultWorksheet.Cells(10, 3 + iSimNumber) = pCalcWorksheet.Cells(11, 10)
'Copies ED $ to output to output
pResultWorksheet.Cells(11, 3 + iSimNumber) = pInputWorksheet.Cells(7, 20 +
iSimNumber) 'Copies LRP $ - a constant to output
pResultWorksheet.Cells(12, 3 + iSimNumber) = pCalcWorksheet.Cells(9, 6)
'Copies HSDG% to output
```

```
pResultWorksheet.Cells(13, 3 + iSimNumber) = pCalcWorksheet.Cells(11, 6)
‘Copies UMG% to output
‘pResultWorksheet.Cells(14, 3 + iSimNumber) =
WorksheetFunction.Sum(pResultWorksheet.Cells(7, 3 + iSimNumber),
pResultWorksheet.Cells(8, 3 + iSimNumber), pResultWorksheet.Cells(9, 3 +
iSimNumber), pResultWorksheet.Cells(10, 3 + iSimNumber),
pResultWorksheet.Cells(11, 3 + iSimNumber))

ThisWorkbook.Worksheets(“Traditional Runs”).Activate
pTradRunsWorksheet.Cells(7 + casenum, 1 + iSimNumber) =
pResultWorksheet.Cells(8, 3 + iSimNumber) ‘Also enter Capacity in UE
scenarios table
ThisWorkbook.Worksheets(“Simulation”).Activate
Next
Next

ThisWorkbook.Sheets(“Output”).Activate
Polished ‘Formats output
‘ResourceChart
Application.Calculation = iOldCalcalculationSetting
Application.StatusBar = False
Application.ScreenUpdating = True
ThisWorkbook.Sheets(“Output”).Activate
ActiveSheet.Cells(1, 1).Select

End Sub
```

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APPENDIX C. PROM-WED USER MANUAL

Planned Resource Optimization Model with Experimental Design

(PROM-WED)

USER MANUAL

Simulation Experiments & Efficient Designs
Center for Data Farming
Naval Postgraduate School

Table of Contents

NOTICE:

The user is cautioned that PROM-WED has not undergone formal verification and validation testing, and comes without any warranty. Informal testing confirms the outputs from PROM-WED match the output from the legacy PRO model.

I. WHAT IS PROM-WED

PROM-WED embeds the legacy PRO model within a data farming environment. The foundation of PROM-WED's data farming wrapper is the nearly orthogonal Latin hypercube (NOLH). The NOLH design of experiments (DOE) builds experimental designs that efficiently and effectively explore the solution space (Cioppa & Lucas, 2007). This good space-filling capability means that uncertainties and fluctuations in input variables along with multivariable interactions can be adequately investigated (Sanchez & Wan, 2015).

The 33 and 129 design point NOLH designs were used to construct PROM-WED's data farming wrapper. The 33-point NOLH DOE tests each variable at 33 levels and grows data for 33 legacy PRO model runs, whereas the 129-point NOLH DOE tests each variable at 129 levels and grows data for 129 legacy PRO model runs. PROM-WED's graphical user interface (GUI) allows users to easily input a range of values for each input variable into the NOLH DOE worksheet, without need for knowledge or familiarity with data farming or DOE techniques (Sanchez, 2011).

A completed PROM-WED excursion grows a data set for either 33 or 129 data points. Automatically generated sensitivity analysis provides users with a basic risk assessment picture focused on the decision variables using the data grown by PROM-WED. Further insights into variable interactions and effects of input variables can be easily explored using available data analysis software. PROM-WED transforms the legacy PRO model into a resource that N1 can use to gain robust insights into the optimal allocation of recruiting resources.

II. OUTPUT OPTIONS

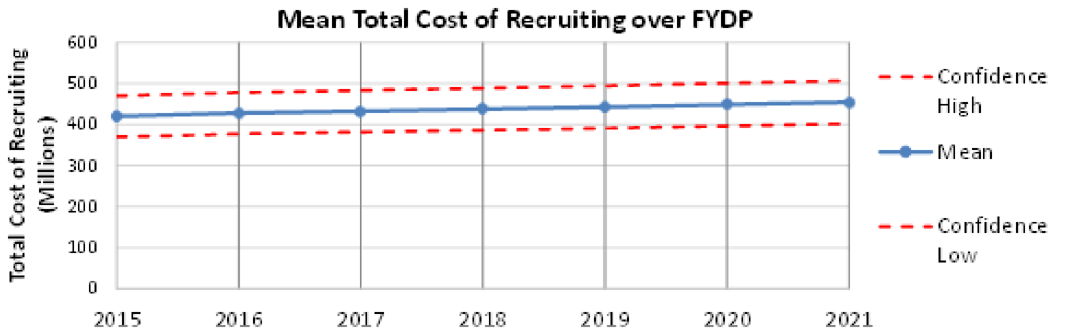
PROM-WED provides users with decision support capabilities to analyze the data grown by each excursion. PROM-WED offers two decision support capabilities: (A) automatically generated analysis, and (B) data generated for further analysis requiring a statistical software package.

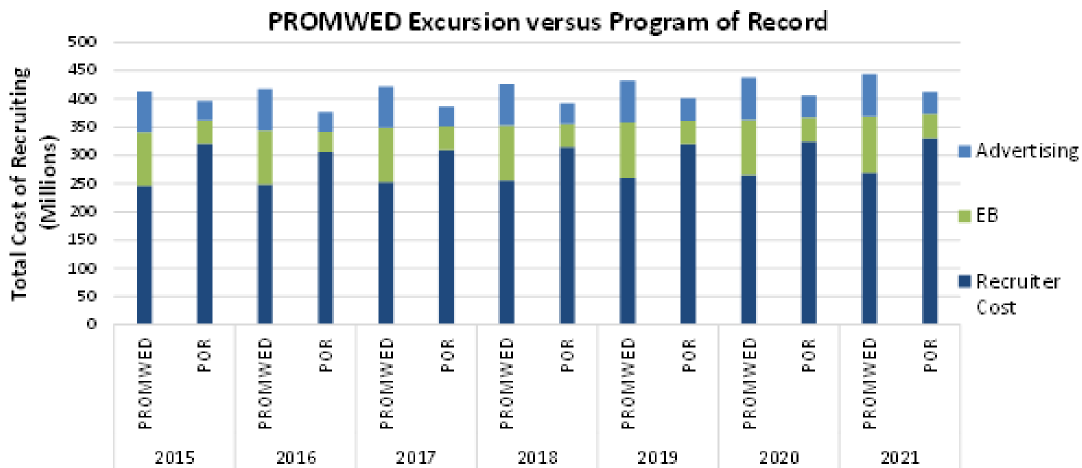
A. AUTOMATICALLY GENERATED ANALYSIS

PROM-WED's "Decision Support Analysis" for the traditional run option provides users with a broad understanding of how variability in decision variables, controllable policy changes, and uncontrollable market factors affect the total cost of recruiting. This type of analysis would be appropriate for testing excursions during a time constrained meeting, working group, or whenever basic analysis needs to be generated quickly.

An example of PROM-WED's automatically generated analysis follows.

Traditional Run: 33 Design Points



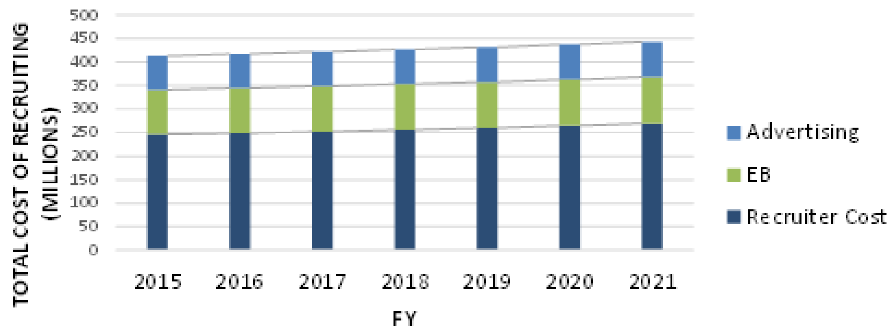


Scenario

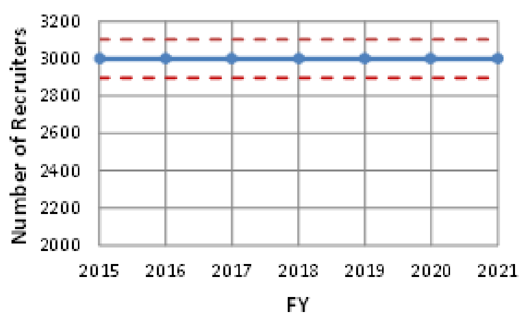
		2015	2016	2017	2018	2019	2020	2021
NCO	high	40000	40000	40000	40000	40000	40000	40000
	low	30000	30000	30000	30000	30000	30000	30000
LRP	high	7.44	11.22	11.28	11.38	11.43	11.46	11.67
	low	7.44	11.22	11.28	11.38	11.43	11.46	11.67
HSDG	high	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	low	0.95	0.95	0.95	0.95	0.95	0.95	0.95
TSC	high	0.85	0.85	0.85	0.85	0.85	0.85	0.85
	low	0.7	0.7	0.7	0.7	0.7	0.7	0.7
UE	high	0.08	0.08	0.08	0.08	0.08	0.08	0.08
	low	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Rel Pay	high	1.2	1.2	1.2	1.2	1.2	1.2	1.2
	low	0.8	0.8	0.8	0.8	0.8	0.8	0.8
QMA	high	1883304	1873304	1863304	1853304	1843304	1833304	1823304
	low	1873304	1863304	1853304	1843304	1833304	1823304	1813304

Decision Variables

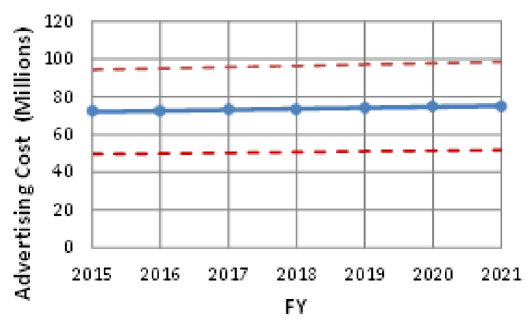
Total Cost of Recruiting



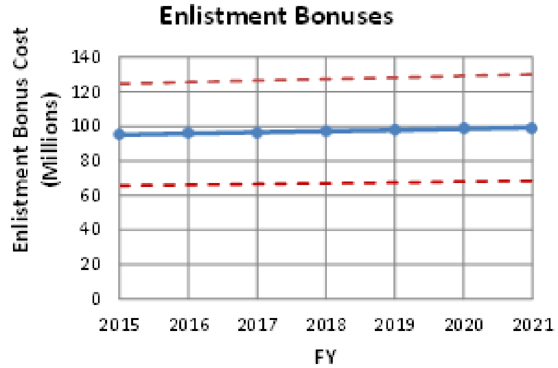
Total Recruiters



Advertising



Enlistment Bonuses

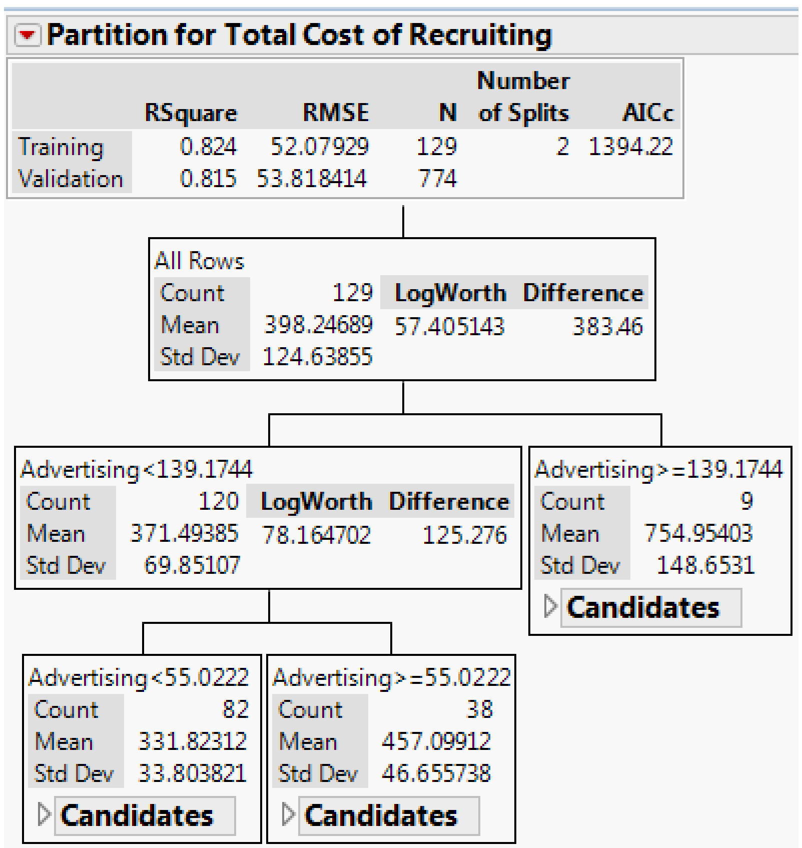


B. JMP ANALYSIS

Analysts will need to use a statistical software package to take full advantage of the data grown by PROM-WED. Therefore, data produced by PROM-WED is designed to be easily uploaded into a software package, such as JMP (JMP Pro, 2015).

The following are examples of insights gained through analysis of PROM-WED data in JMP.

1. Partition Tree



Over 80 percent of variance in the total cost of recruiting is explained by the amount of funds allocated to advertising.

2. Stepwise Regression

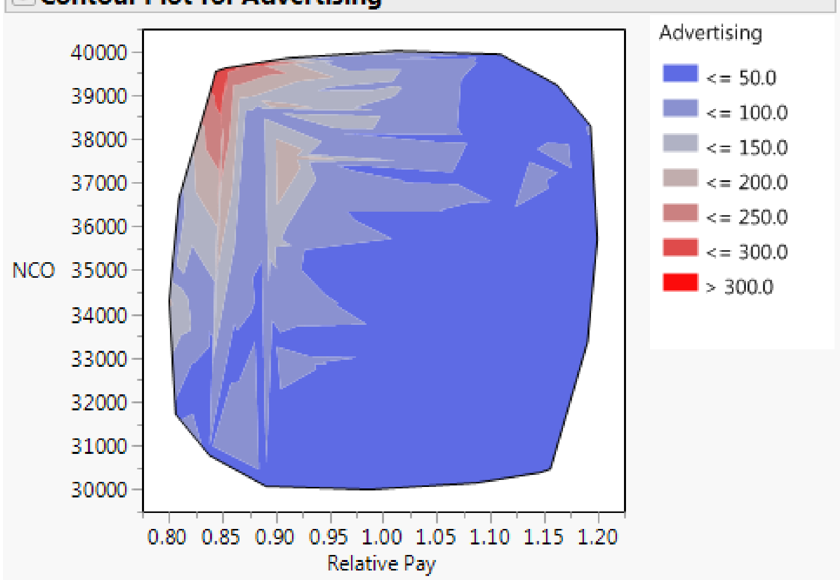
The total cost of recruiting can be formulated into a stepwise regression model:

Prediction Expression

$$
\begin{aligned}
&150.980052850998 \\
&+ 0.02553596931337 * \text{NCO} \\
&+ -24.593679044673 * \text{Unemployment} \\
&+ -550.34801858165 * \text{Relative Pay} \\
&+ \left(\text{NCO} - 35000.0620155039\right) * \left(\left(\text{Relative Pay} - 1\right) * -0.1270005027034\right) \\
&+ \left(\text{NCO} - 35000.0620155039\right) * \left(\left(\text{NCO} - 35000.0620155039\right) * 0.00000304992539\right) \\
&+ \left(\text{Relative Pay} - 1\right) * \left(\left(\text{Relative Pay} - 1\right) * 1882.37625427676\right)
\end{aligned}
$$

3. Contour Plots

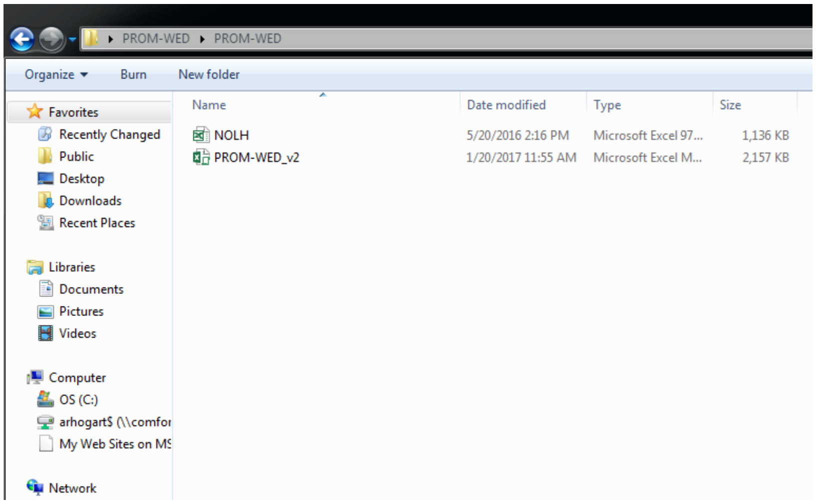
Contour Plot for Advertising



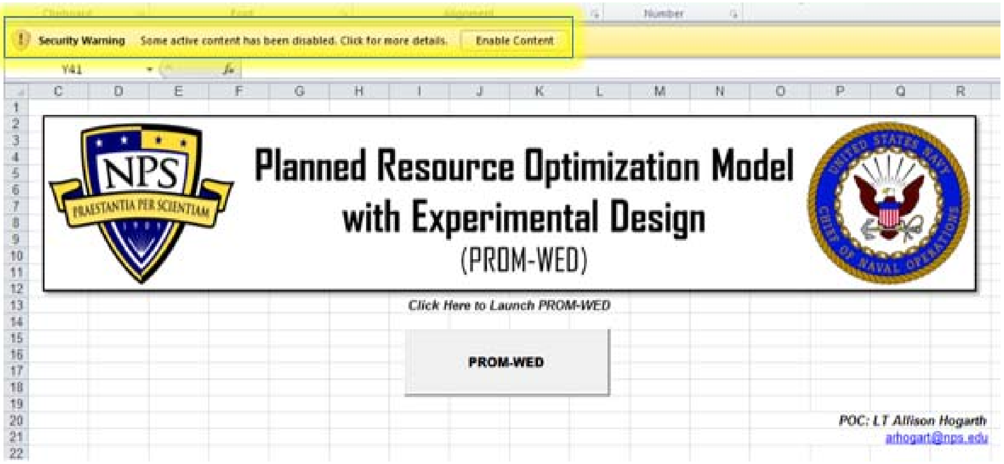
The contour plot indicates that nearly half of the solution space supports a low advertising budget, represented by the dark blue region. The cost of advertising substantially increases when relative pay favors the civilian sector and the accession mission is high, represented by the red region. Once relative pay exceeds approximately 1.00, changes in the new accession mission have little to no effect on the amount of resources allocated to advertising.

III. STEP-BY-STEP INSTRUCTIONS TO RUN PROM-WED

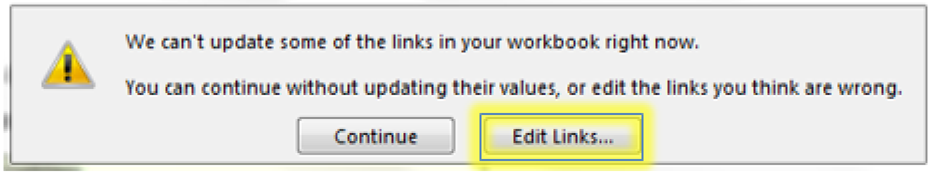
Step 1: Unzip the "PROM-WED.zip" file, and save the "PROM-WED.xlsm" file and "NOLH.xls" file in the same folder. This folder is where the output file generated by PROM-WED will be saved following the PROM-WED excursion.



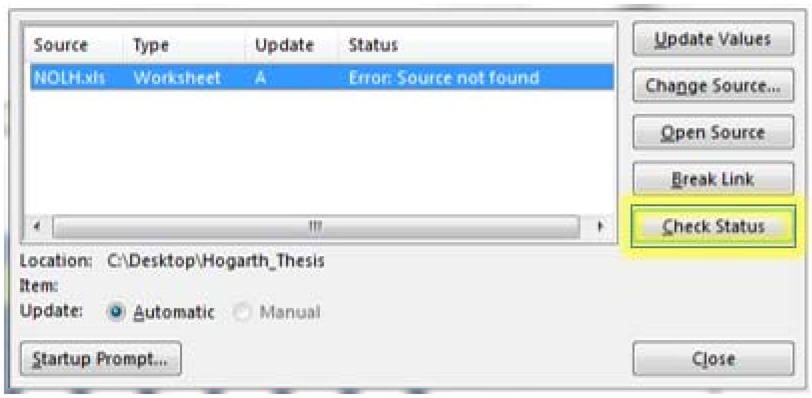
Step 2: Open the PROM-WED file, and ensure the "Enable Content" button is selected.



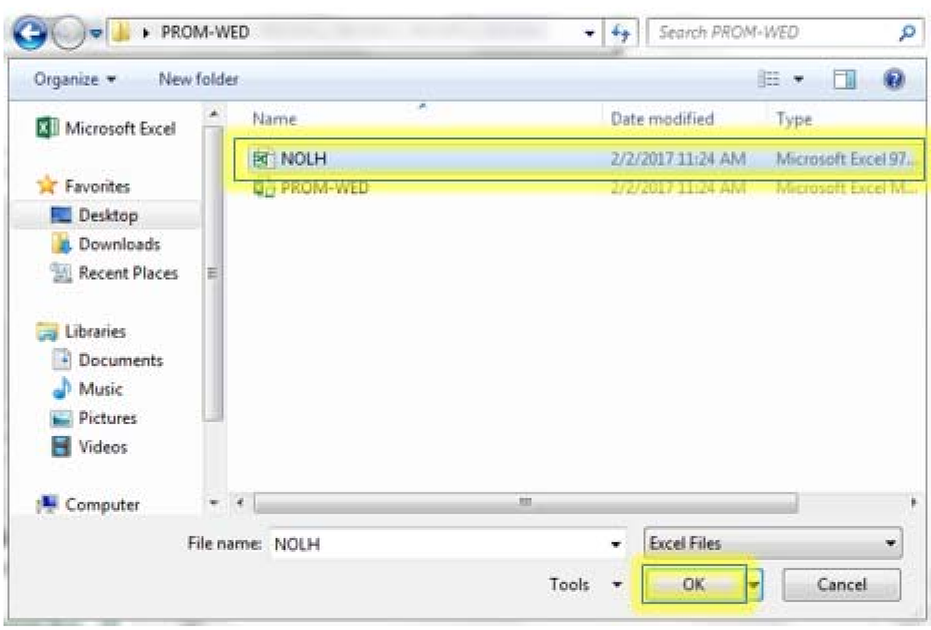
The first time you open PROM-WED, the NOLH.xls file link needs to be updated. To do this, select the “Edit Links...” button.



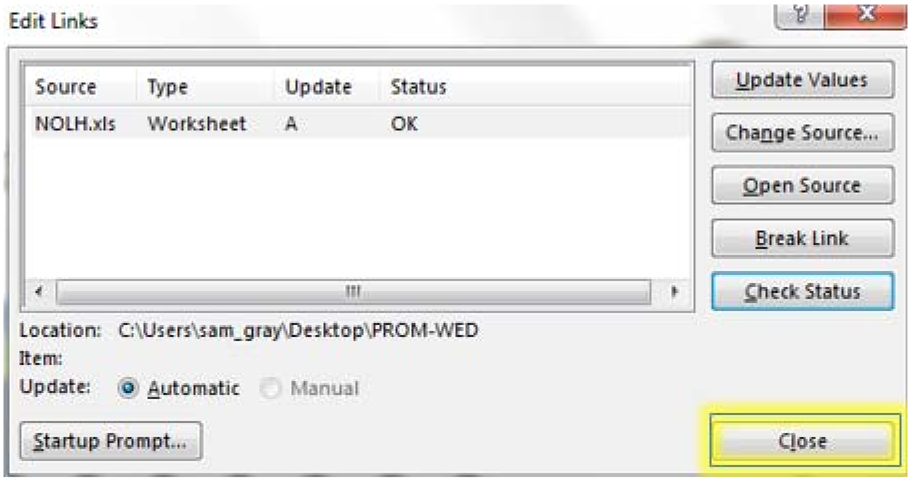
To update the NOLH.xls file, click on the “Change Source…” button.



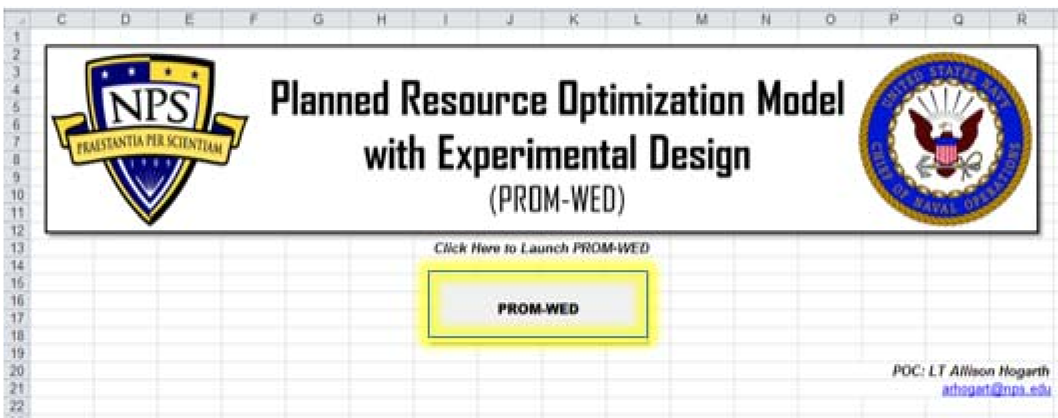
A file search window will pop-up. Navigate to the folder where you saved the files after unzipping them. Select the “NOLH.xls” file, and click on the “OK” button.



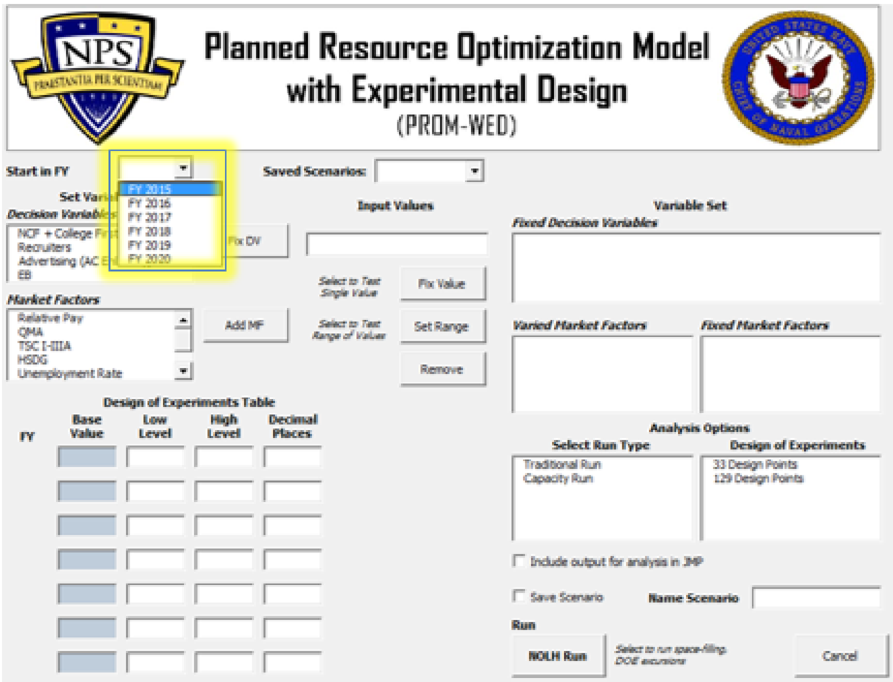
The “Edit Links” window will pop-up. Once the “NOLH.xls” worksheet’s status updates to “OK,” click on the “Close” button.



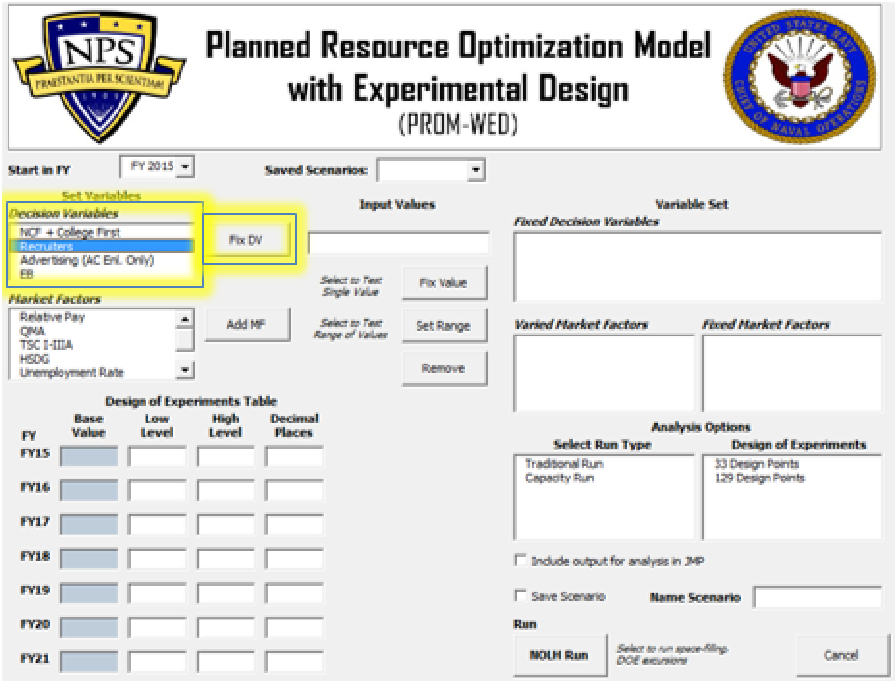
Step 3: Open the PROM-WED file, and select the “PROM-WED” button to open the GUI.



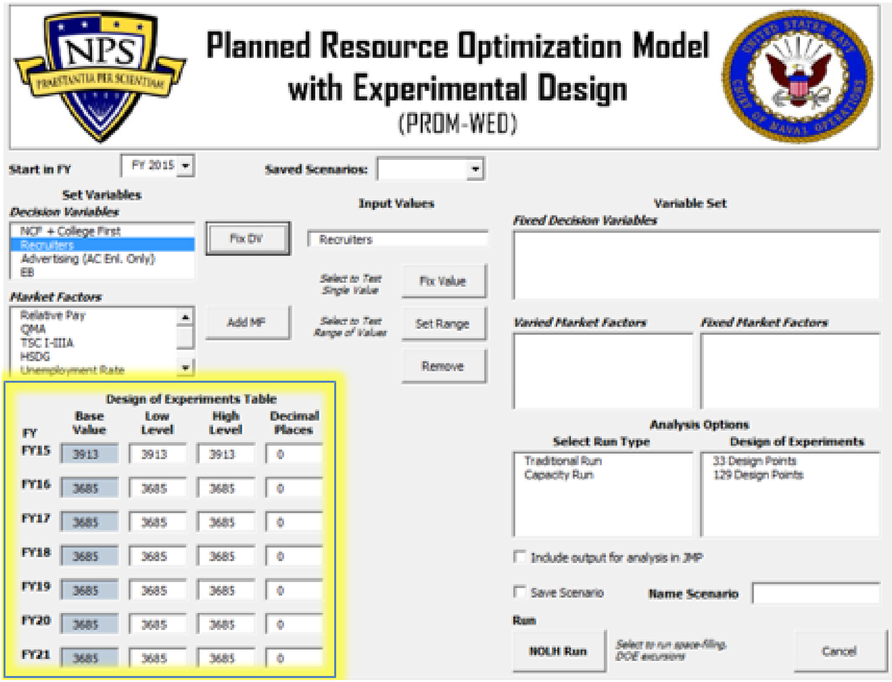
Step 4: Select the appropriate starting fiscal year (FY) from the drop-down list. The current version of the legacy PRO model is set at a FY 2015 start.



Step 5: To constrain a decision variable, select it from the list, and click “Fix DV” button.



The default data from the legacy PRO Model will automatically populate the “Design of Experiments Table.”

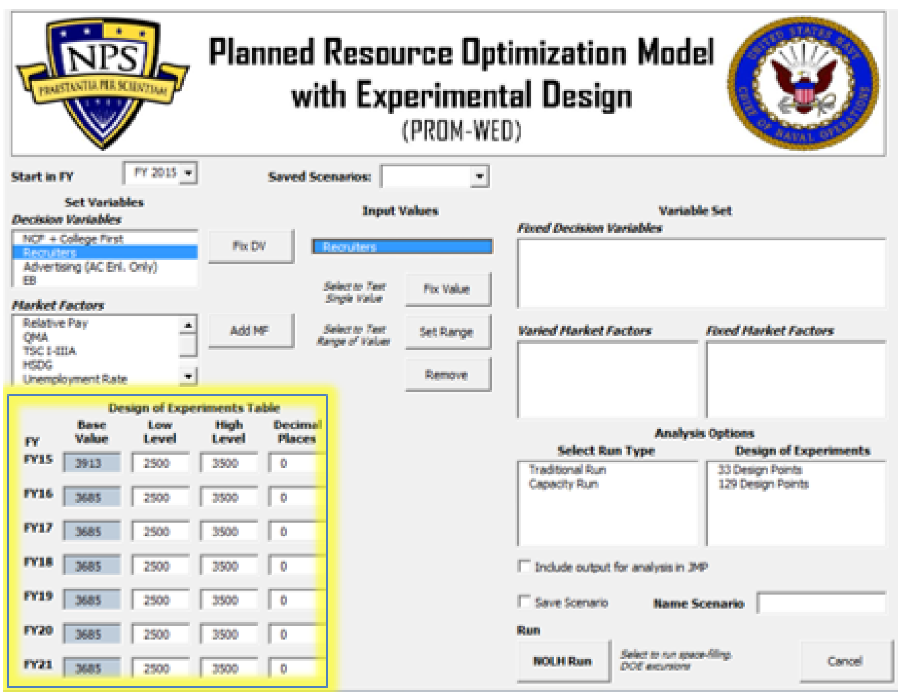


Step 6: Input the range of values for the decision variable in the “Design of Experiments Table.” Input the low value of the range in the “Low Level” text box for each FY, and the high value of the range in the “High Level” text box for each FY. In this example, the number of recruiters is tested from 2,500 to 3,500 for each FY.

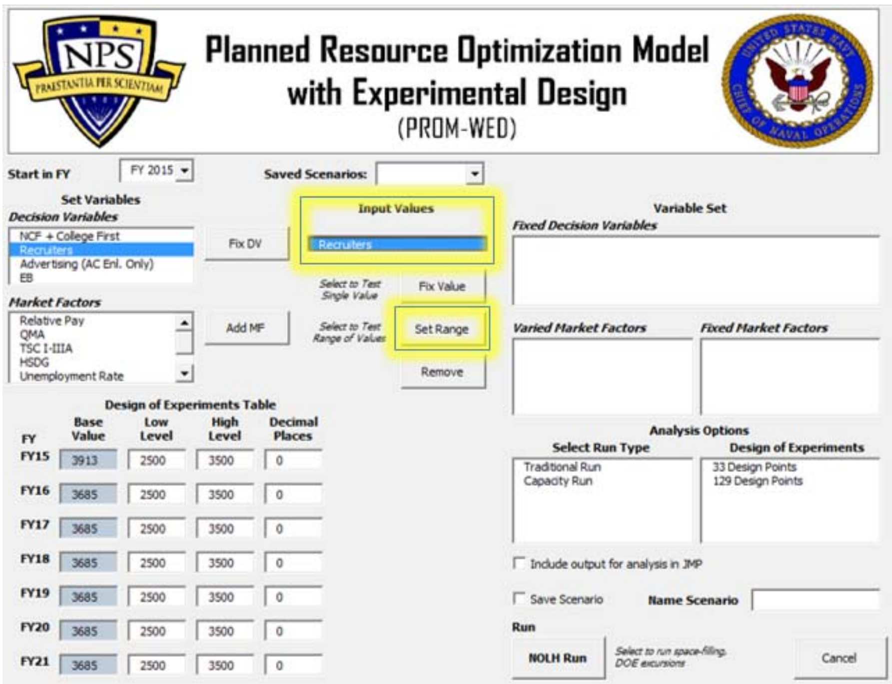
Each year can be tested using different ranges. For example, to represent a smaller recruiter force in FY 2021, the range could be inputted as 2,000 to 2,700.

If you want to constrain the decision variable at the default value populated by the legacy PRO model, select the “Fix Value” button. By selecting “Fix Value,” the default values for the decision variable in the “Design of Experiments Table” are deposited into the NOLH worksheet for each FY. This decision variable is now moved to the “Fixed Decision Variables” list, and the “Design of Experiments Table” is cleared. (If this is your course of action, continue to Step 8.)

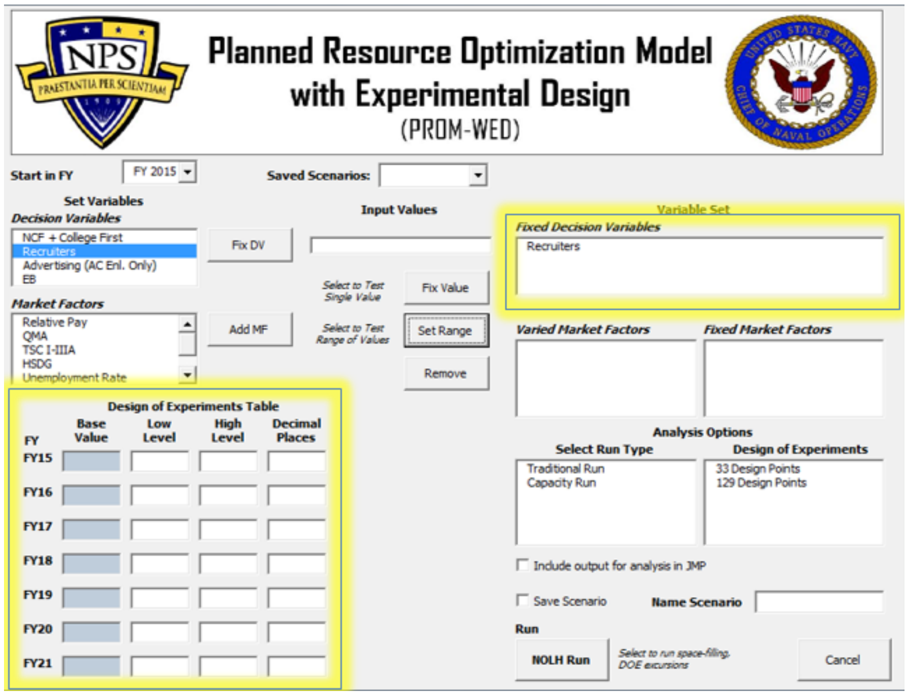
If you want to constrain the decision variable at one number that is different than the default value populated by the legacy PRO model, the same number has to be inputted into the “Low Level” and “High Level” text boxes. For example, if you want to constrain the number of recruiters in FY 2021 to 2700, then you would enter 2700 in both the “Low Level,” and “High Level” text boxes.



Step 7: Once the "Design of Experiments Table" is fully populated with the low and high levels for each FY, select the decision variable from the "Input Values" box, and click on the "Set Range" button.



By selecting "Set Range," the low and high values entered for this decision variable in the "Design of Experiments Table" are deposited into the NOLH worksheet for each FY. This decision variable is now moved to the "Fixed Decision Variables" list, and the "Design of Experiments Table" is cleared.



Step 8: Follow Steps 5–7 to fix any other decision variables.

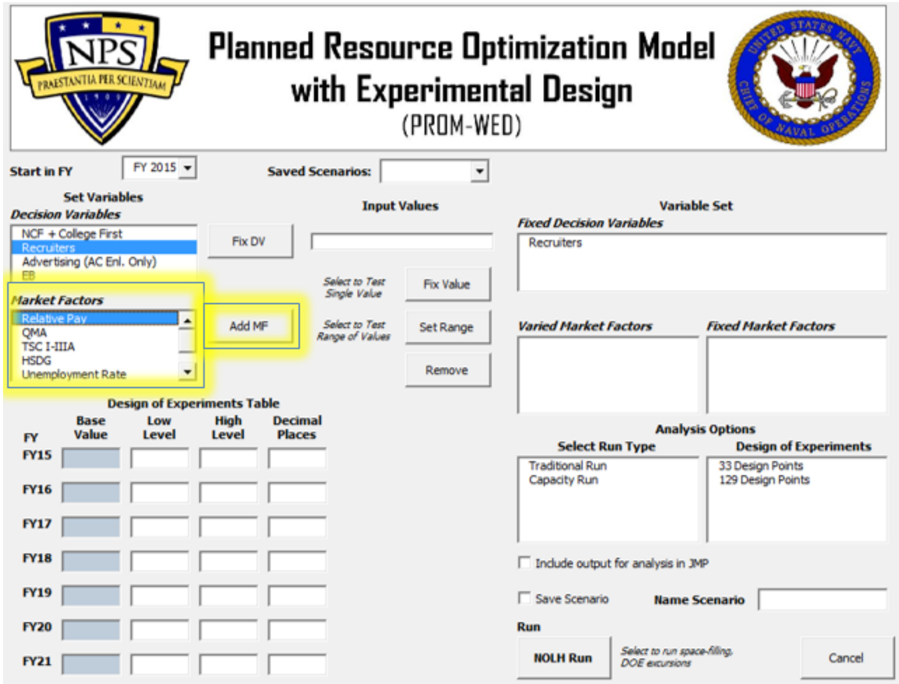
Reminders:

- If you constrain a decision variable to a number other than the default values populated from the legacy PRO model, as mentioned earlier enter the same number into the low and high level text boxes, and select the “Set Range” button when complete.

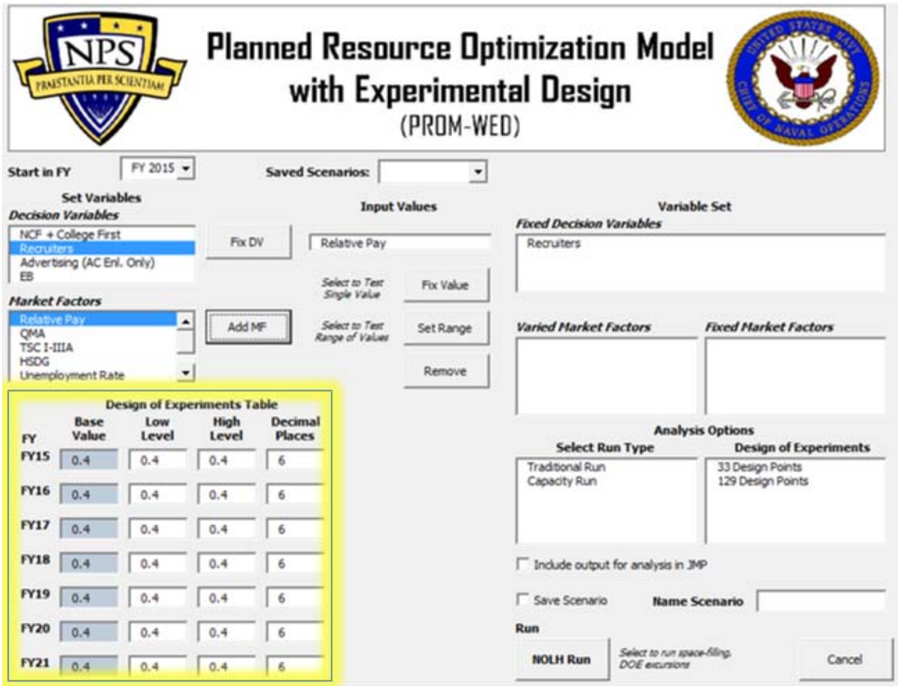
- Since the PRO model solves an optimization problem, ensure that at least one of the following decision variables: Recruiters, Advertising or Enlistment Bonus (EB) remain in a “float” status. In this example, only the number of recruiters are fixed.

Step 9: Once all decision variables that need to be fixed are fixed, gears shift to the market factors. The "Market Factors" list includes all market factors (relative pay, QMA and unemployment rate) and policy factors (percentage of high quality recruits (TSC I-IIIA), percentage of recruits with a high school diploma (HSDG), and NCO). Each market factor, from relative pay to NCO, must either be fixed at one value, or a range of values needs to be entered.

Similar to how decision variables are fixed, select "Relative Pay" from the list of market factors, and select the "Add MF" button.

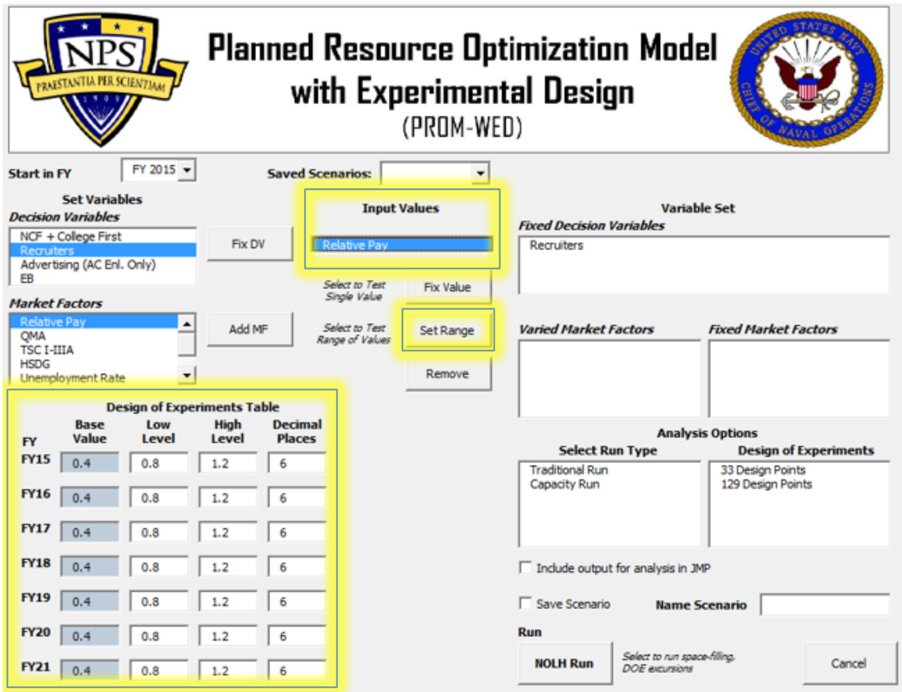


The default data from the legacy PRO Model automatically populates in the “Design of Experiments Table.”

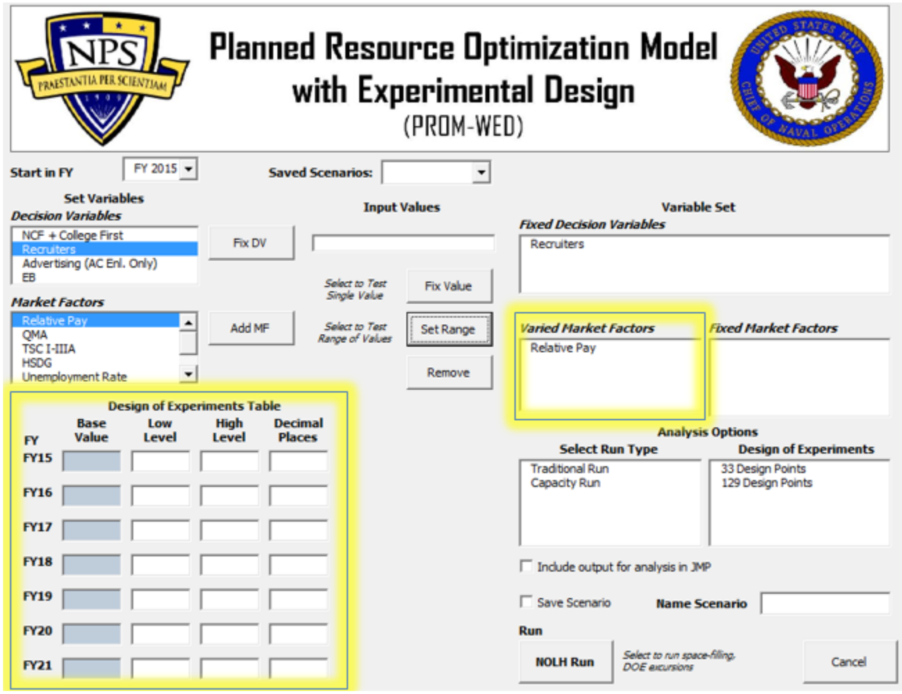


Step 10: Input the range values for the market factor in the “Design of Experiments Table.” Input the low value of the range in the “Low Level” text box for each FY, and the high value of the range in the “High Level” text box for each FY.

In this example, the relative pay is tested from 0.8 to 1.2 for each FY. Clicking the “Set Range” button deposits the low and high values entered for this market factor into the NOLH worksheet for each FY.



This market factor is now moved to the "Varied Market Factors" list, and the "Design of Experiments Table" is cleared.



Step 11: Work through each "Market Factor" in the list, from "Relative Pay" to "NCO" following Steps 9–10.

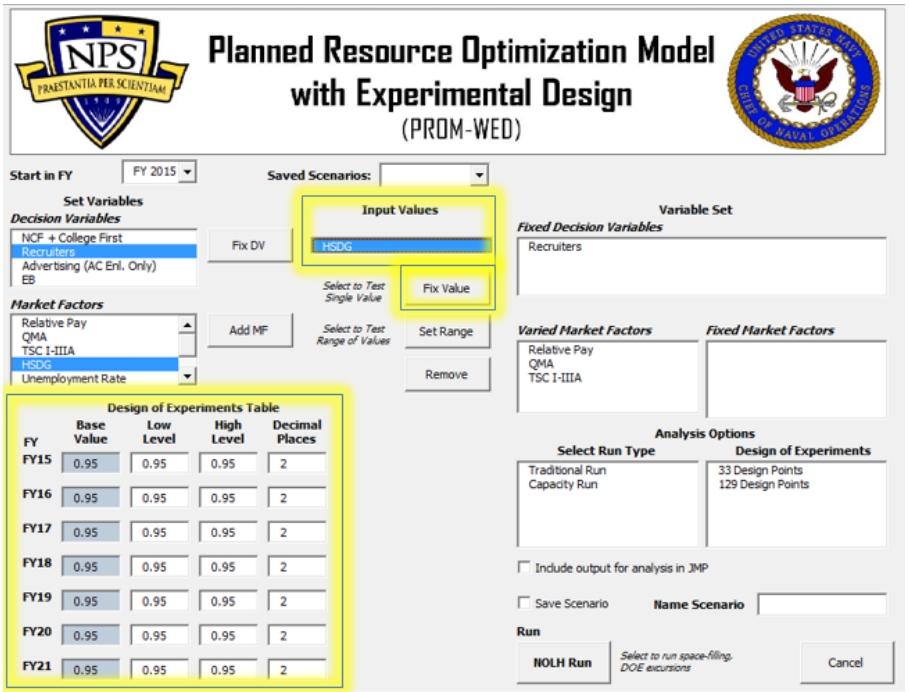
Note that each year can be tested using a different range of values for the market factors. For example, an annual decrease of 10,000 QMA can be entered as shown in the figure below.

Design of Experiments Table

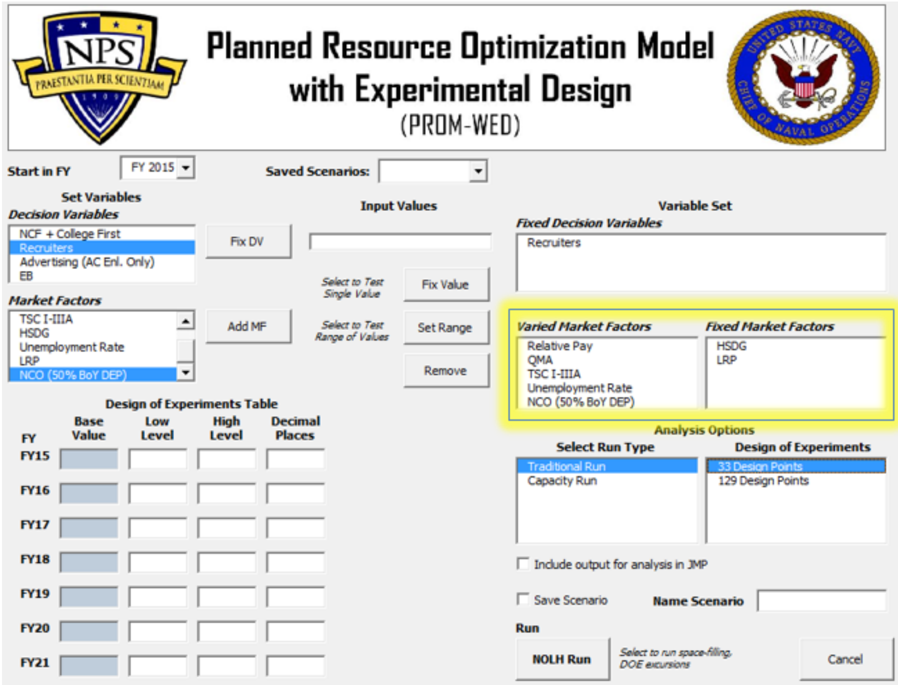
FY	Base Value	Low Level	High Level	Decimal Places
FY15	1883304	1873304	1883304	0
FY16	1883304	1863304	1873304	0
FY17	1883304	1853304	1863304	0
FY18	1883304	1843304	1853304	0
FY19	1883304	1833304	1843304	0
FY20	1883304	1823304	1833304	0
FY21	1883304	1813304	1823304	0

If you want to constrain the market factor at one number different than what is populated by the legacy PRO model, the same number has to be inputted into the "Low Level" and "High Level" text boxes. Then select the "Set Range" button.

To constrain the market factor at the value automatically populated in the "Design of Experiments Table," select the market factor from the "Input Values" box, and click on the "Fix Value" button.



Step 12: Work through all seven market factors until they are all accounted for. A market factor is accounted for once it appears in either the "Varied Market Factors," or "Fixed Market Factors" lists.



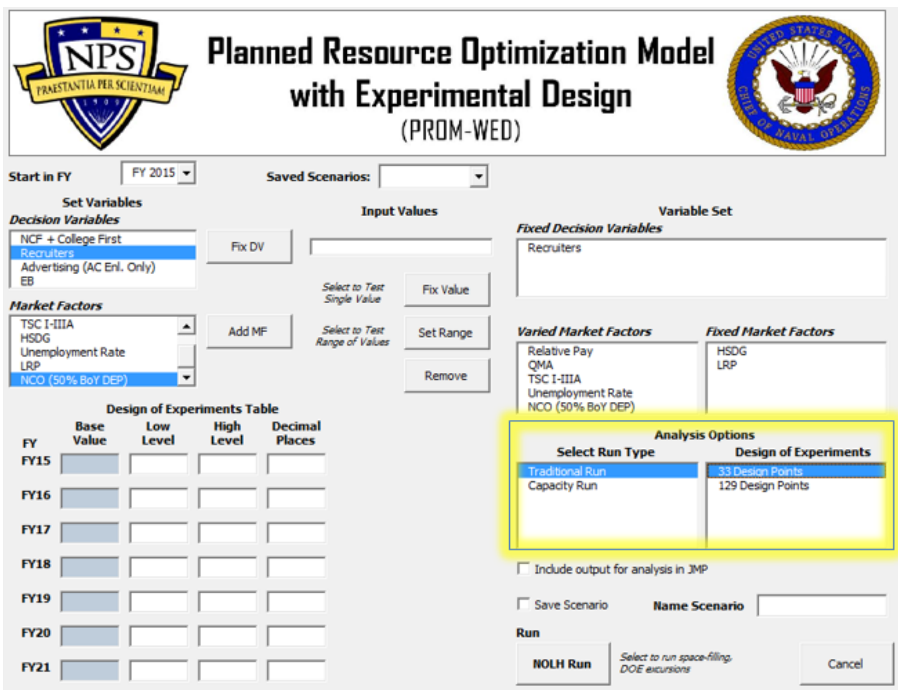
Step 13: Select "Traditional Run" under "Select Run Type." (Currently, only the Traditional Run option is operational).

<u>Automatically Generated Decision Support</u>:

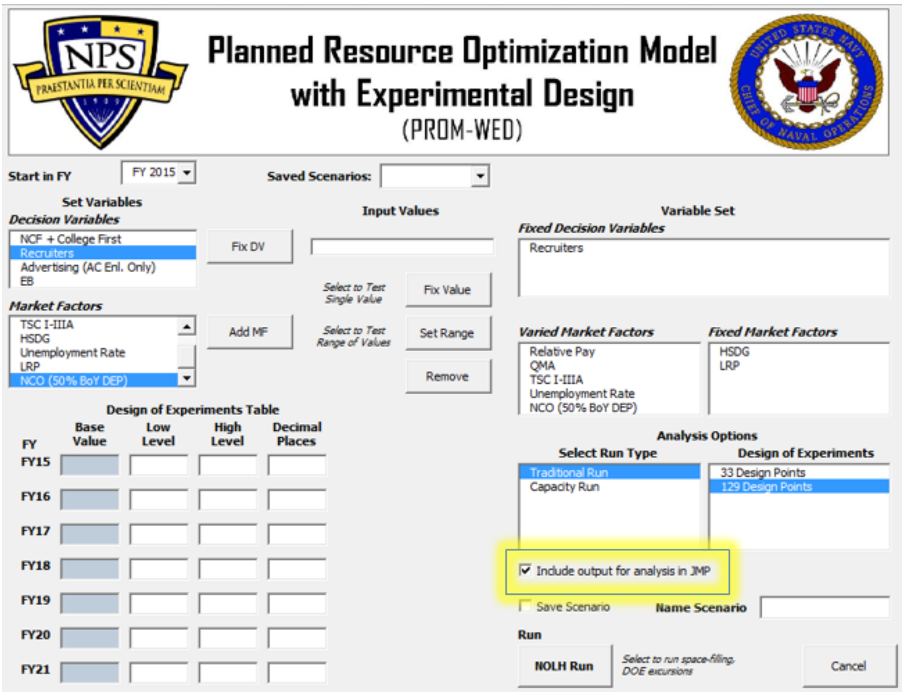
The "33 Design Points" option is well suited for the automatically generated decision support analysis. The "129 Design Points" option can also be used, but it will take additional time to run (approximately 10 minutes versus 2–3 minutes). The "129 Design Points" option grows more data, resulting in a narrower 95% confidence interval.

<u>Analysis in JMP:</u>

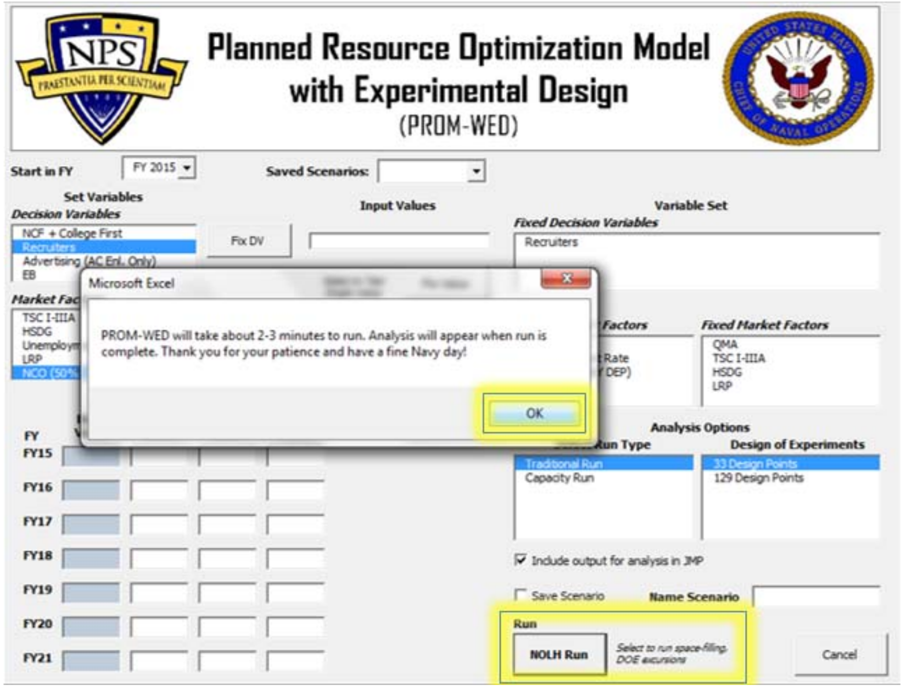
The "129 Design Points" option is intended to be used for further analysis in a commercial statistical software package, such as JMP.



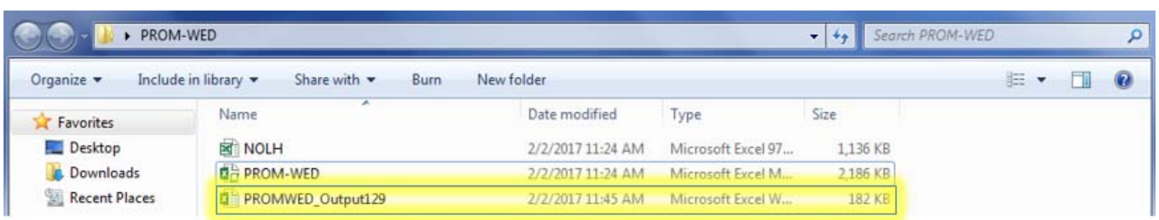
Step 14: To save PROM-WED output to a separate .xls file for analysis in JMP, select the "Include output for analysis in JMP" box. This will save the PROM-WED output as a .xls file in the same folder that the PROM-WED model was saved in.



Step 15: Once the run options are set, select the "NOLH Run" button. A message will pop-up providing an estimated wait time for the PROM-WED excursion. Click "OK."



Step 16: When the PROM-WED excursion is complete, the automatically generated decision support analysis will appear (this is true for both the 33 and 129 point designs). If you selected the option to output PROM-WED data for analysis in JMP, the .xls file named "PROMWED_Output129.xls" will appear in the folder that your PROM-WED model is saved in.



Please be aware that each 129 design point output file will be named "PROMWED_Output129.xls." It is recommended that you rename the file before running another PROM-WED excursion.

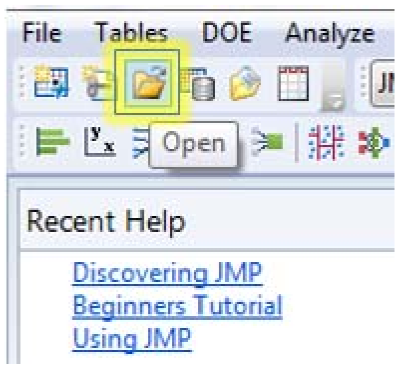
IV. GUIDELINES FOR ANALYSIS OF PROM-WED DATA IN JMP

Using JMP Pro 12, the following section provides a tutorial on analysis techniques for PROM-WED output. Steps 1–5 explain how to upload and prepare the data for analysis in JMP, followed by guidance on how to conduct various analysis techniques.

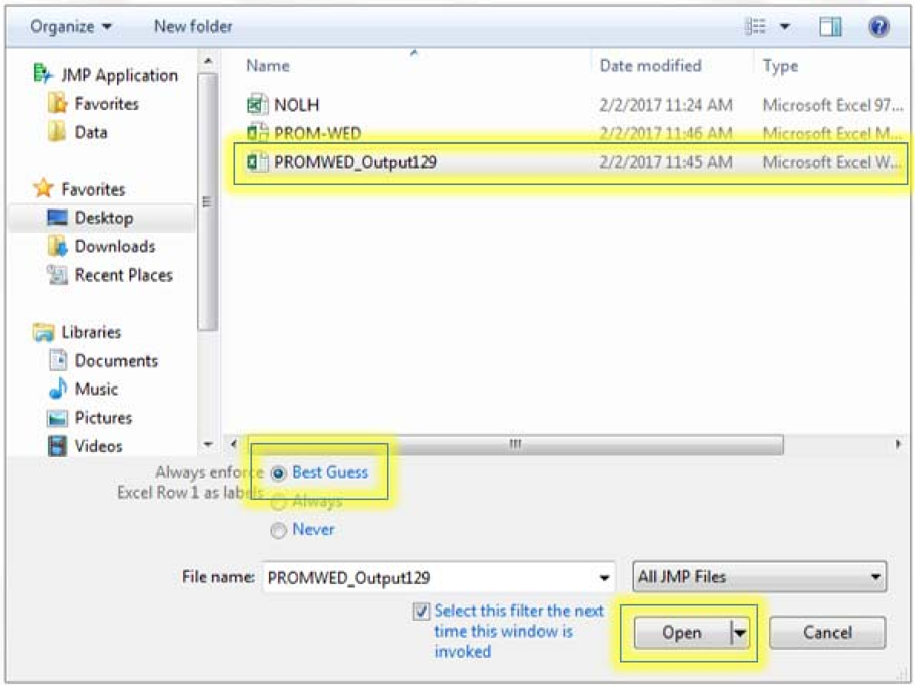
Analysis Techniques:

A. Oneway Analysis of Total Cost of Recruiting by FY
B. Explore Outliers from the Oneway Analysis Graph
C. Select one FY to Analyze
D. Distribution
E. Partition Trees
F. Stepwise Regression Model
G. Scatterplot Matrix
H. Contour Plot

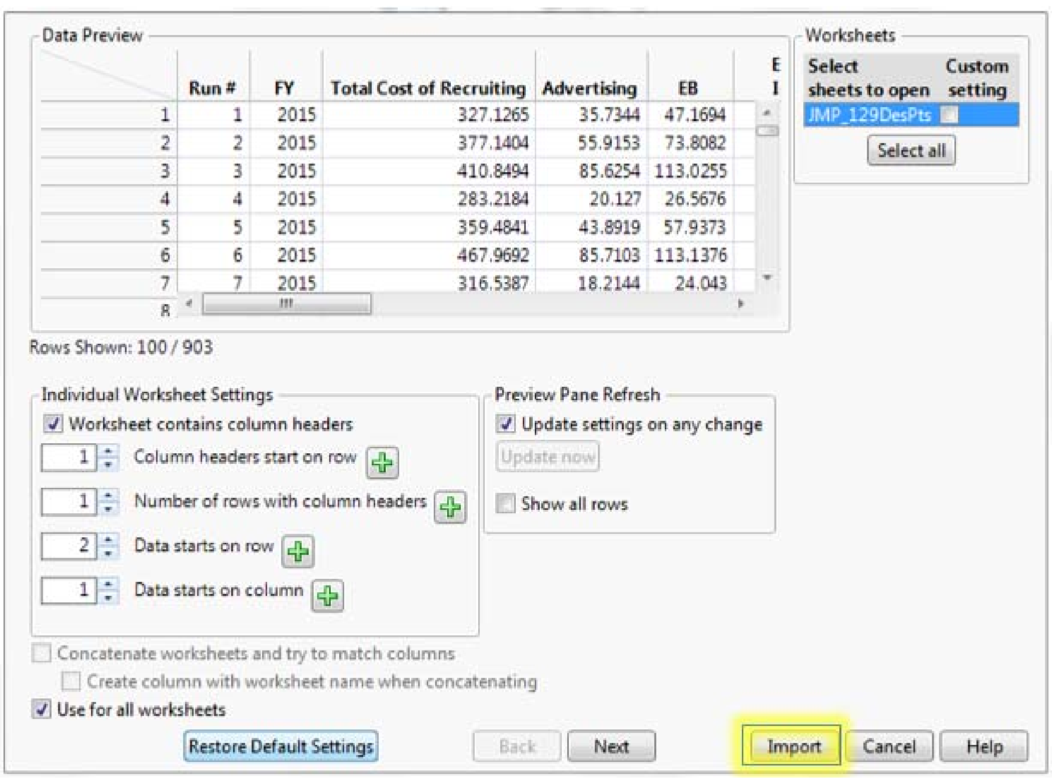
Step 1: To load the PROM-WED data into JMP, select the folder icon.



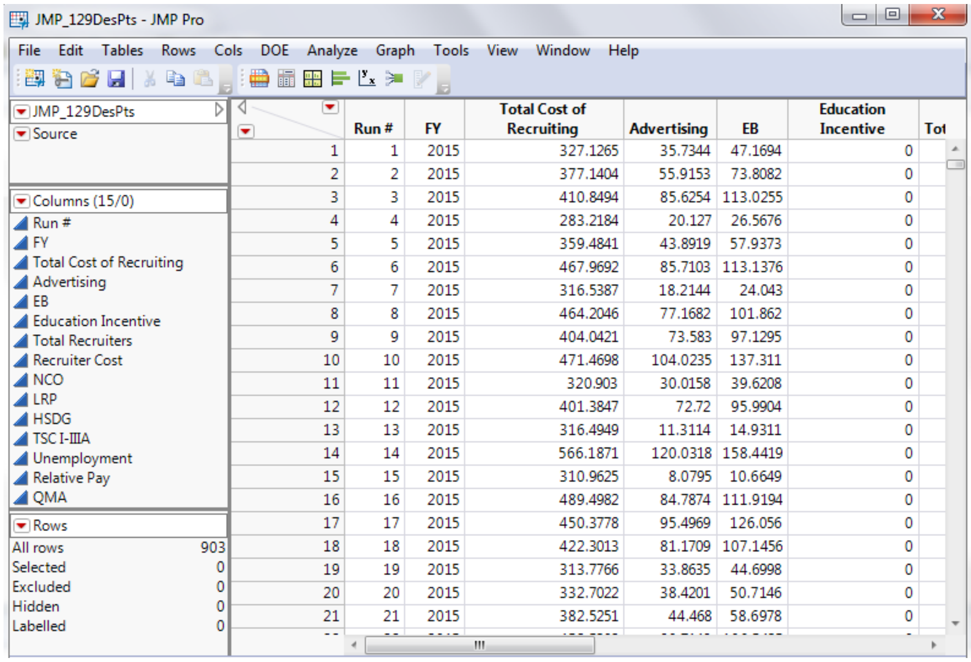
Step 2: Select the output data of interest, select the "Best Guess" option, and click "Open."



Step 3: Select the "Import" button.

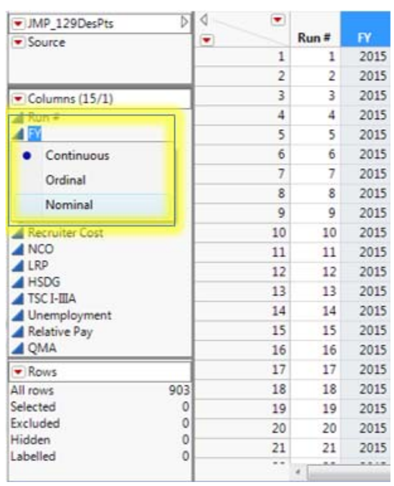


The PROM-WED output data should appear in a table, as shown below:

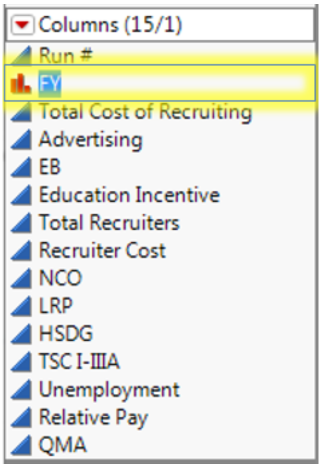


	Run #	FY	Total Cost of Recruiting	Advertising	EB	Education Incentive	Tot
1	1	2015	327.1265	35.7344	47.1694	0	
2	2	2015	377.1404	55.9153	73.8082	0	
3	3	2015	410.8494	85.6254	113.0255	0	
4	4	2015	283.2184	20.127	26.5676	0	
5	5	2015	359.4841	43.8919	57.9373	0	
6	6	2015	467.9692	85.7103	113.1376	0	
7	7	2015	316.5387	18.2144	24.043	0	
8	8	2015	464.2046	77.1682	101.862	0	
9	9	2015	404.0421	73.583	97.1295	0	
10	10	2015	471.4698	104.0235	137.311	0	
11	11	2015	320.903	30.0158	39.6208	0	
12	12	2015	401.3847	72.72	95.9904	0	
13	13	2015	316.4949	11.3114	14.9311	0	
14	14	2015	566.1871	120.0318	158.4419	0	
15	15	2015	310.9625	8.0795	10.6649	0	
16	16	2015	489.4982	84.7874	111.9194	0	
17	17	2015	450.3778	95.4969	126.056	0	
18	18	2015	422.3013	81.1709	107.1456	0	
19	19	2015	313.7766	33.8635	44.6998	0	
20	20	2015	332.7022	38.4201	50.7146	0	
21	21	2015	382.5251	44.468	58.6978	0	

Step 4: Change the FY column from "continuous" to "nominal" data, by right-clicking on the blue triangle next to "FY," and select "nominal" from the drop-down menu.

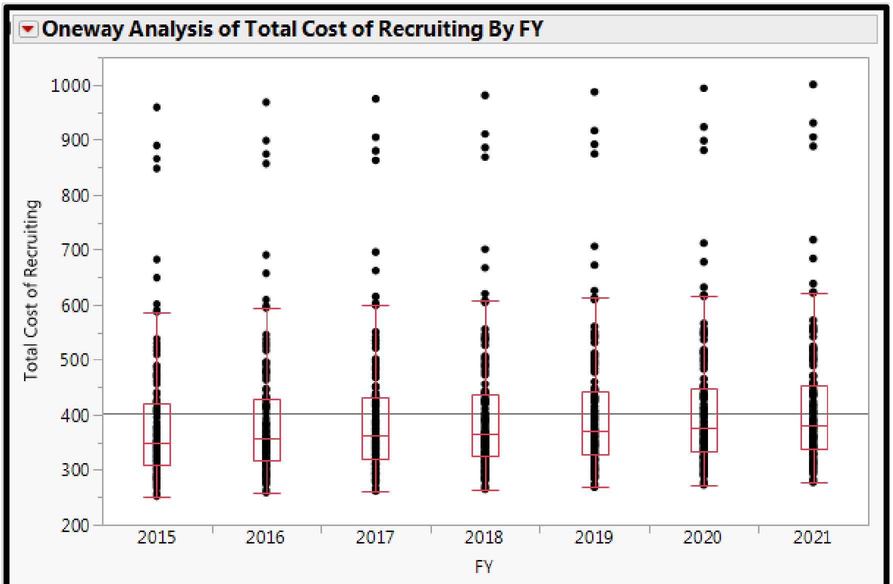


The blue triangle next to FY will change to a red bar chart icon when JMP changes its classification to nominal data.



The data is now ready to be analyzed.

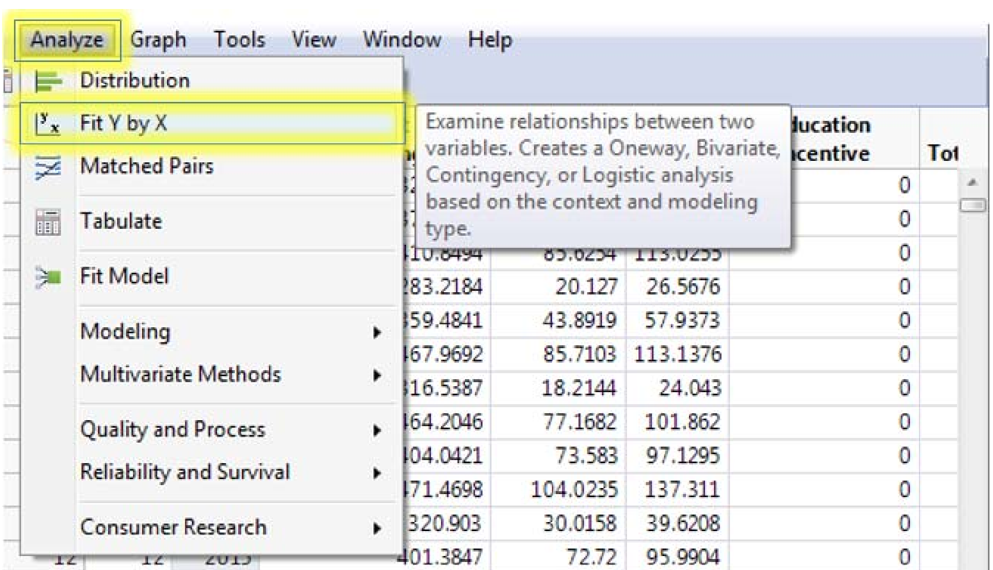
A. ONEWAY ANALYSIS OF TOTAL COST OF RECRUITING BY FY



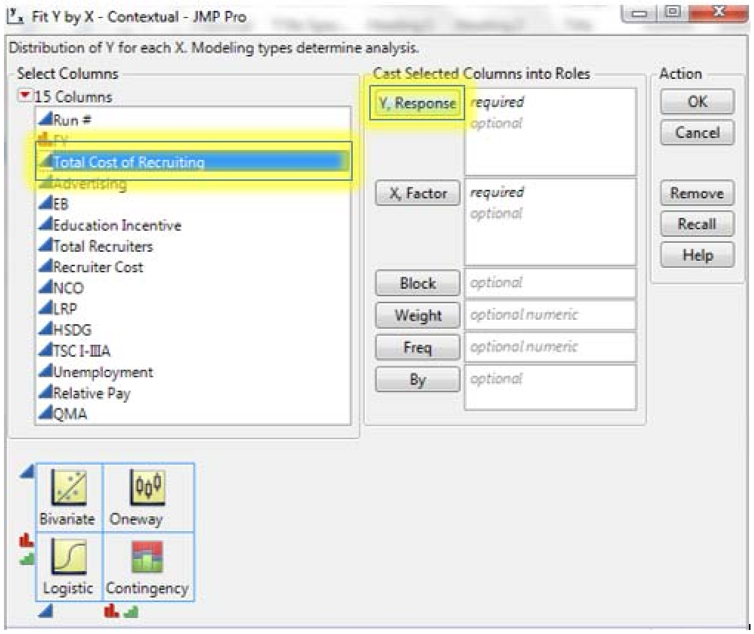
Quantiles

Level	Minimum	10%	25%	Median	75%	90%	Maximum
2015	251.8643	283.3929	309.1051	349.9401	421.2093	521.9235	959.1079
2016	258.138	289.8711	315.9455	356.89	428.4688	529.2777	968.0586
2017	261.6095	293.5959	320.1883	361.2135	433.1215	533.85	974.1696
2018	265.1709	297.4278	324.5511	365.861	437.8086	538.5172	980.3789
2019	268.7332	301.3375	329.0443	370.5412	442.3917	543.1901	986.5974
2020	272.8857	305.6795	334.2964	375.5285	447.5582	548.4681	993.3847
2021	277.2888	310.3785	339.8189	380.7692	453.0851	554.0022	1000.43

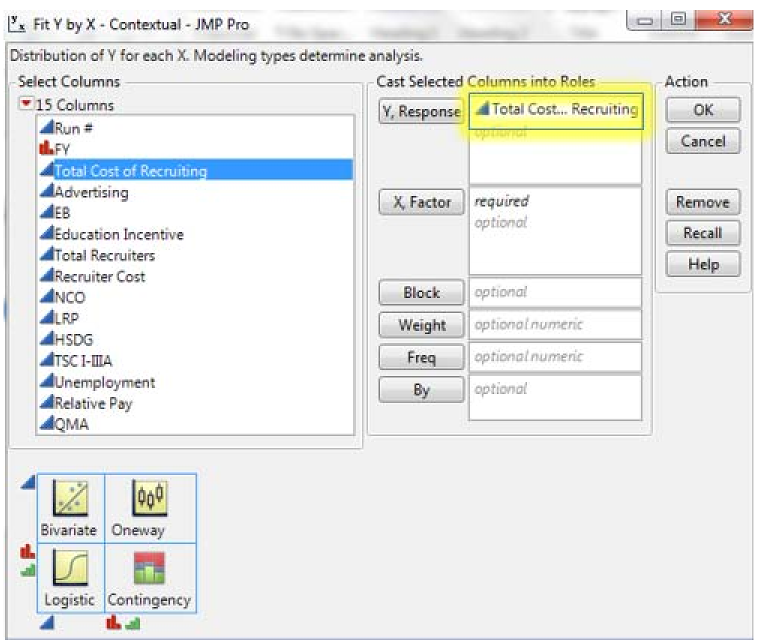
Step 1: To create an oneway analysis of total cost of recruiting by FY graph, select “Analyze” from the ribbon, and select “Fit Y by X.”



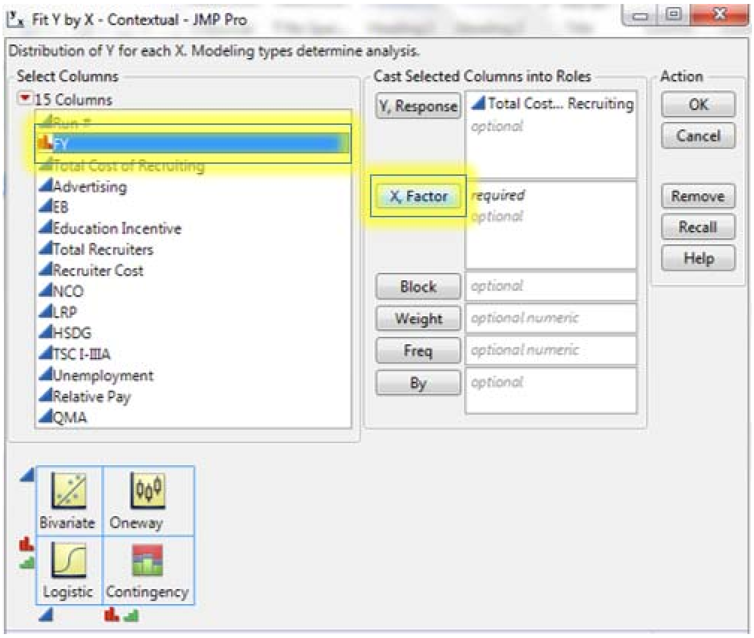
Step 2: Select "Total Cost of Recruiting" from the list of columns, and select the "Y, Response" button.



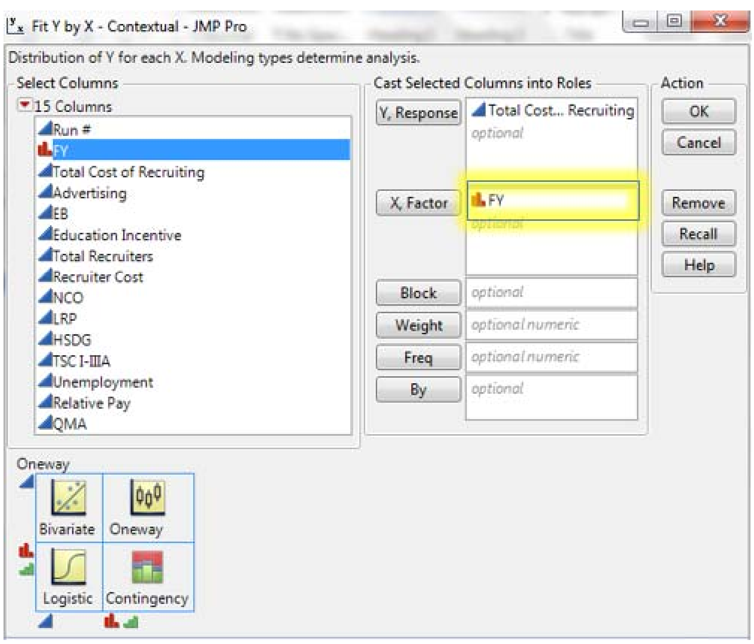
"Total Cost of Recruiting" should now appear in the "Y, Response" box.



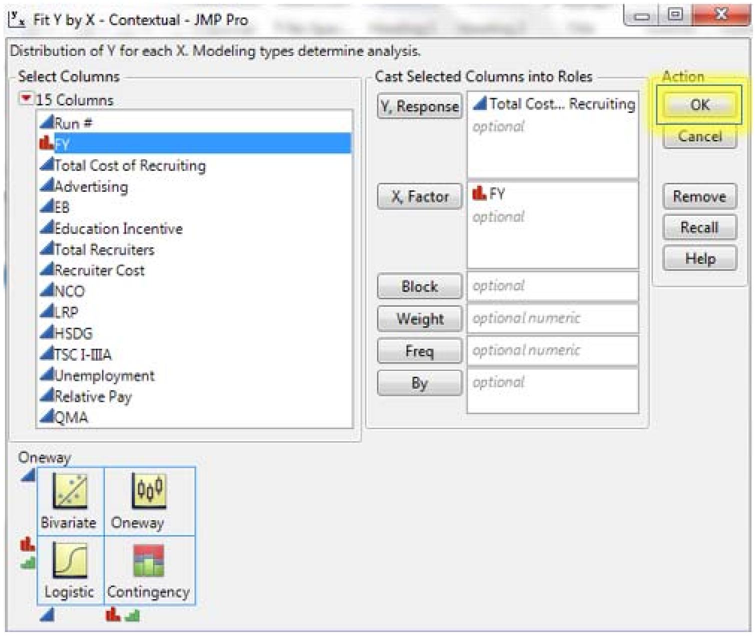
Step 3: Select "FY" from the list of columns, and select the "X, Factor" button.



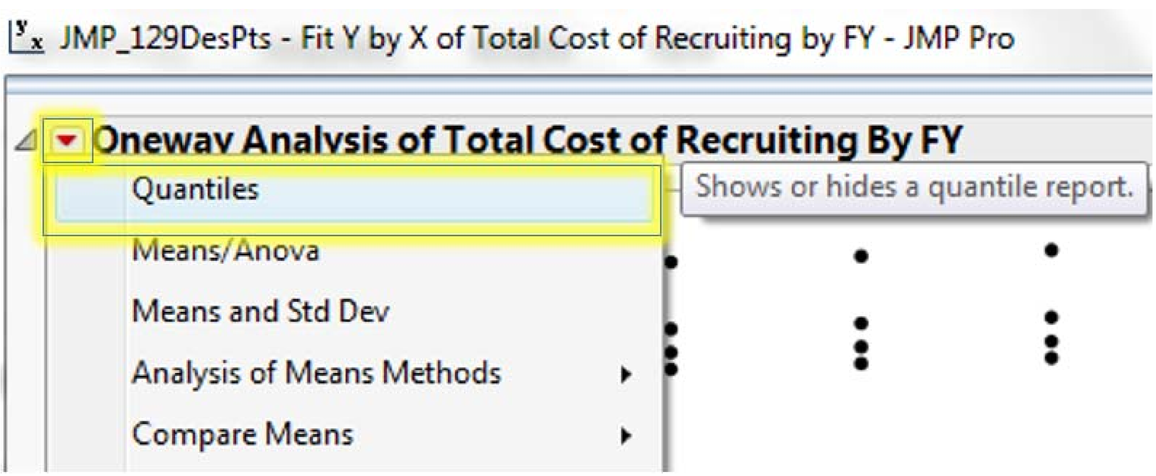
"FY" should now appear in the "X, Factor" box.



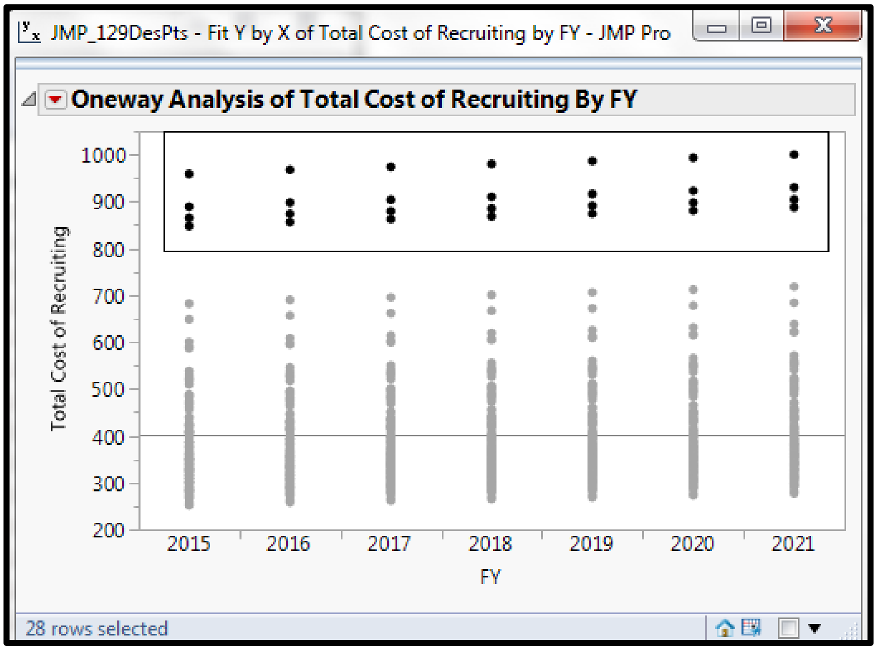
Step 4: Click-on the “OK” button to generate the graph of FY by total cost of recruiting.



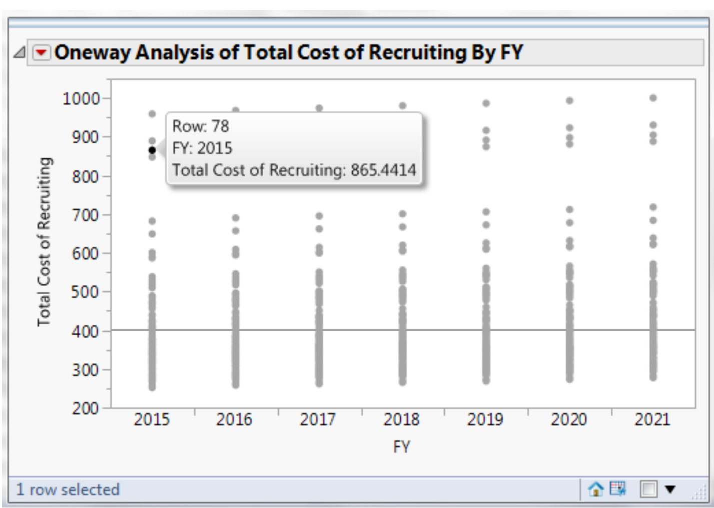
Step 5: To add boxplots on the data for each FY, select the red triangle in the upper left hand corner of the graph. From the drop-down menu, select “Quantiles.”



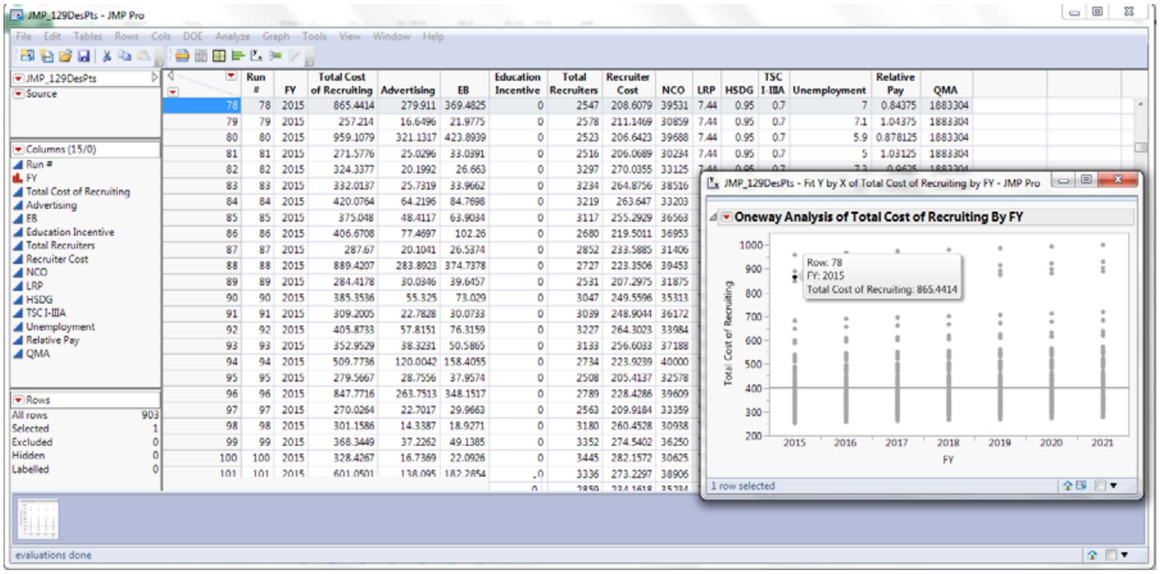
B. EXPLORE OUTLIERS FROM THE ONEWAY ANALYSIS GRAPH



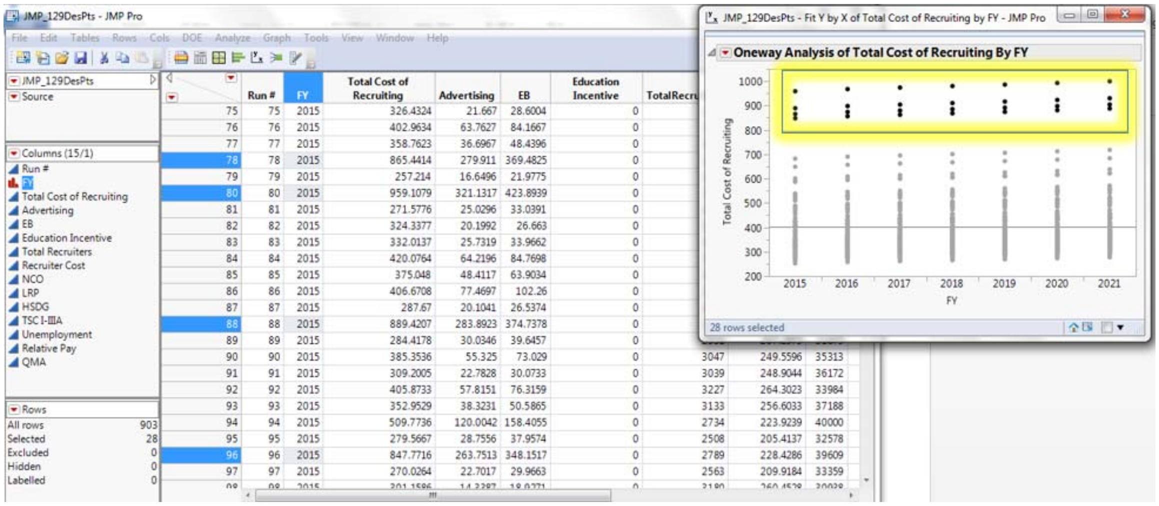
Step 1: Hover your mouse over a data point of interest to retrieve information regarding that point.



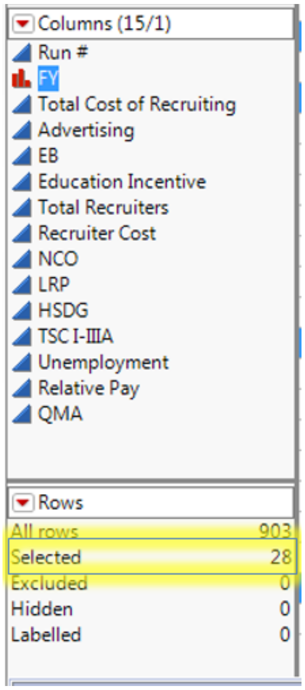
Clicking on the data point on the graph will highlight it within the greater data set. Understanding the input variables can help explain why the total cost of recruiting was unusually high for this data point.



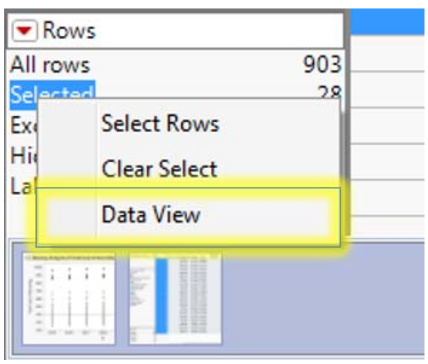
Step 2: To explore a group of outliers, lasso the data points of interest by creating a box around the data points with your mouse. Lassoing the data points will automatically select these data points within the greater data set.



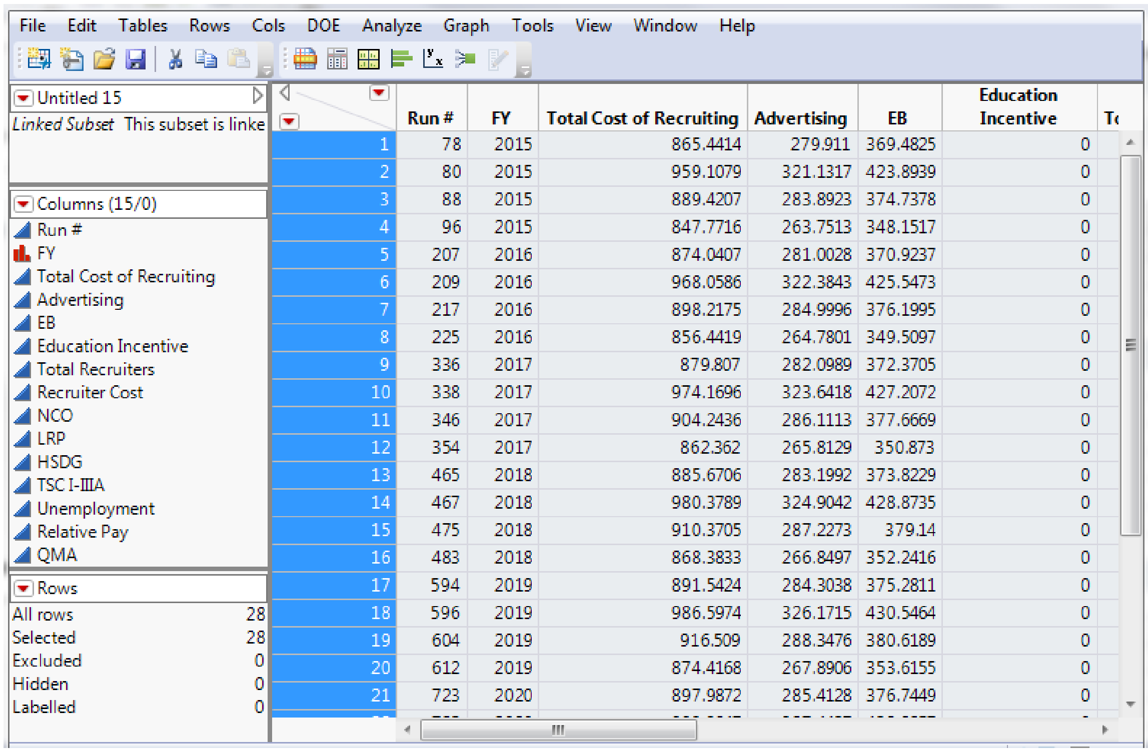
Step 3: The selected data points can be further analyzed on their own. Right-click on "Selected."



Then choose "Data View" from the drop down menu.



This will create a separate data table with just the outliers.

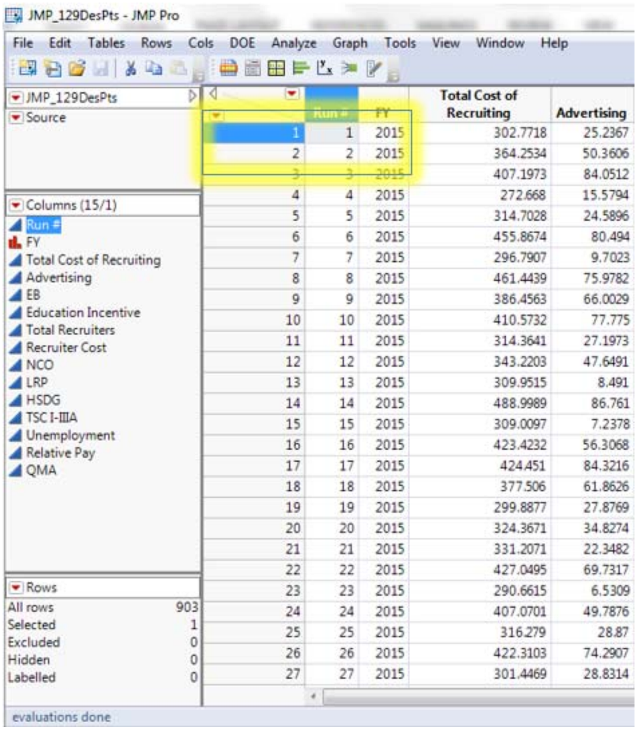


	Run #	FY	Total Cost of Recruiting	Advertising	EB	Education Incentive	To
1	78	2015	865.4414	279.911	369.4825	0	
2	80	2015	959.1079	321.1317	423.8939	0	
3	88	2015	889.4207	283.8923	374.7378	0	
4	96	2015	847.7716	263.7513	348.1517	0	
5	207	2016	874.0407	281.0028	370.9237	0	
6	209	2016	968.0586	322.3843	425.5473	0	
7	217	2016	898.2175	284.9996	376.1995	0	
8	225	2016	856.4419	264.7801	349.5097	0	
9	336	2017	879.807	282.0989	372.3705	0	
10	338	2017	974.1696	323.6418	427.2072	0	
11	346	2017	904.2436	286.1113	377.6669	0	
12	354	2017	862.362	265.8129	350.873	0	
13	465	2018	885.6706	283.1992	373.8229	0	
14	467	2018	980.3789	324.9042	428.8735	0	
15	475	2018	910.3705	287.2273	379.14	0	
16	483	2018	868.3833	266.8497	352.2416	0	
17	594	2019	891.5424	284.3038	375.2811	0	
18	596	2019	986.5974	326.1715	430.5464	0	
19	604	2019	916.509	288.3476	380.6189	0	
20	612	2019	874.4168	267.8906	353.6155	0	
21	723	2020	897.9872	285.4128	376.7449	0	

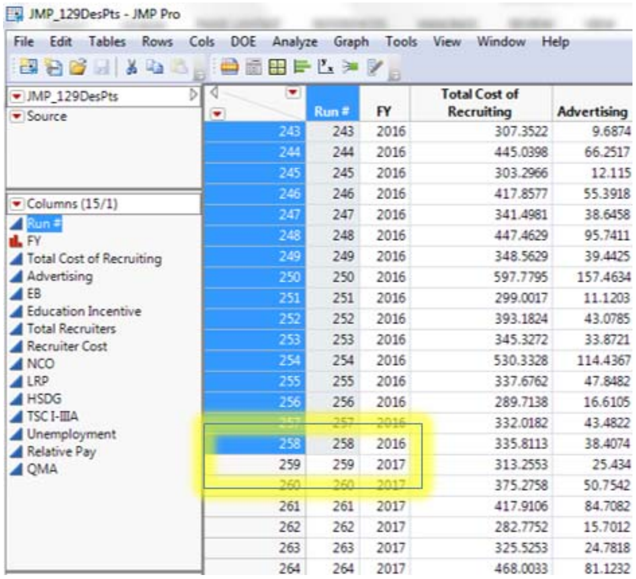
C. SELECT ONE FY TO ANALYZE

To focus analysis on one specific FY, the other six FYs must be hidden and excluded. In this example, FY 2017 is the FY of interest. FYs 2015, 2016, 2018, 2019, 2020, and 2021 will be hidden and excluded.

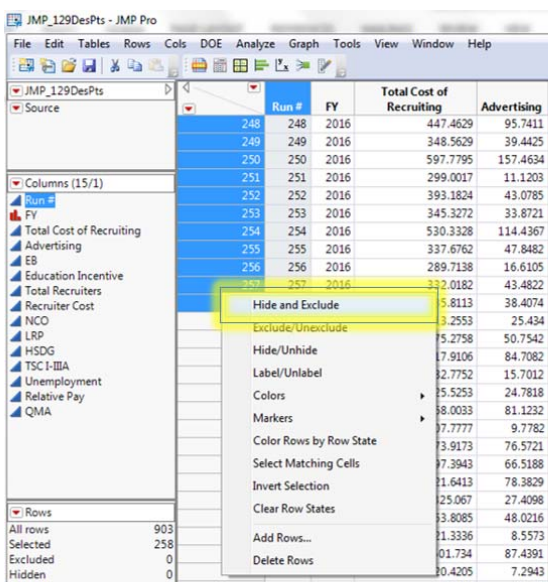
Step 1: To exclude FY 2015 and 2016, select on the first row of FY 2015 data in the furthest column to the left. Hold the “shift” keyboard button.

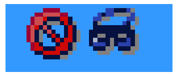


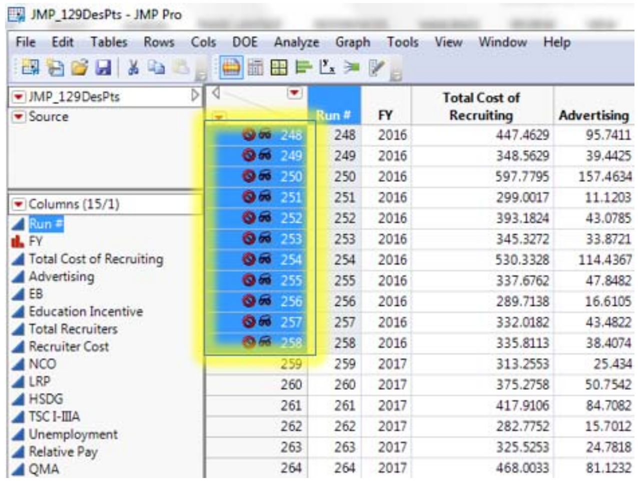
Step 2: Scroll down to the last row of FY 2016 data (which appears in row "258"). Click on the "258" cell in the furthest column to the left.



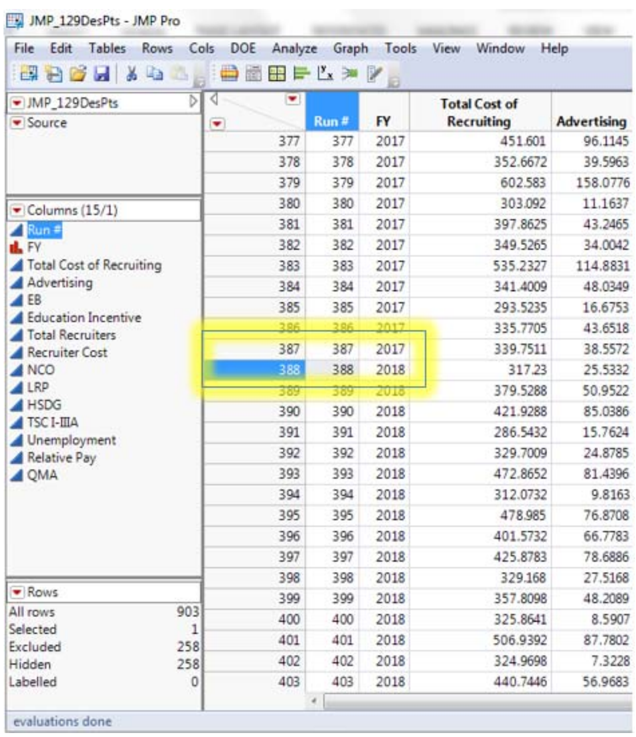
Step 3: Right-click on the selected rows, and choose "Hide and Exclude" from the drop down menu.



You should now see  next to each row of data from FY 2015 and 2016.

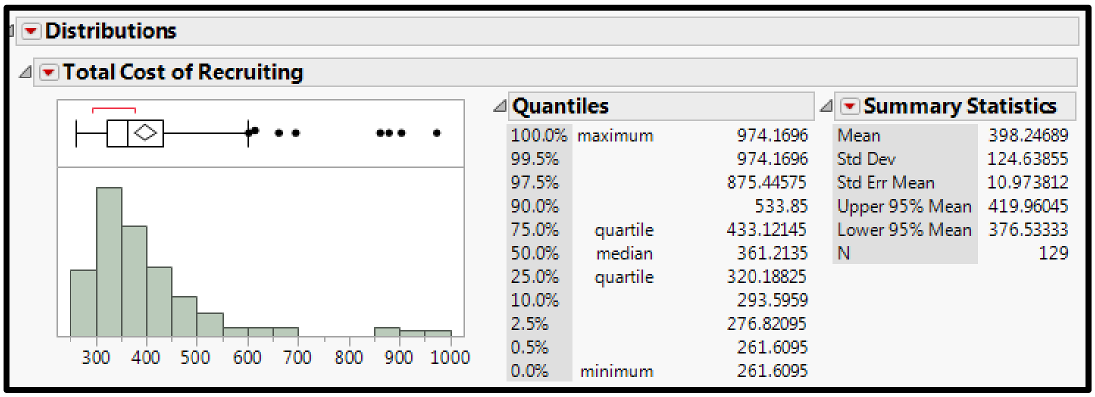


Step 4: Follow steps 1–3 to hide and exclude data from FY 2018, 2019, 2020 and 2021. Row 388 is the first row of data for FY 2018.

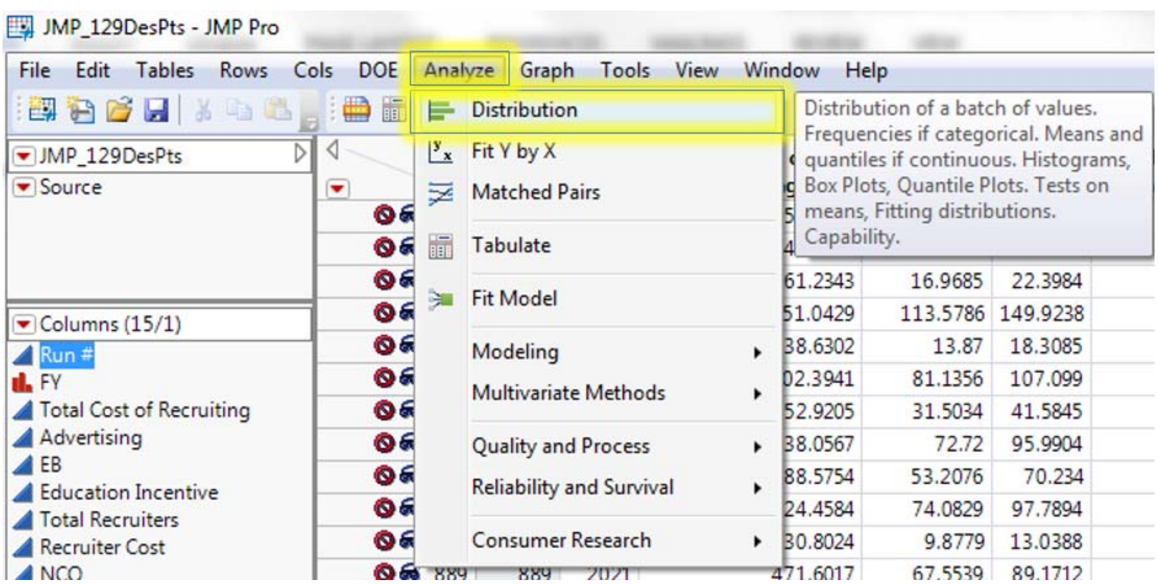


D. DISTRIBUTION

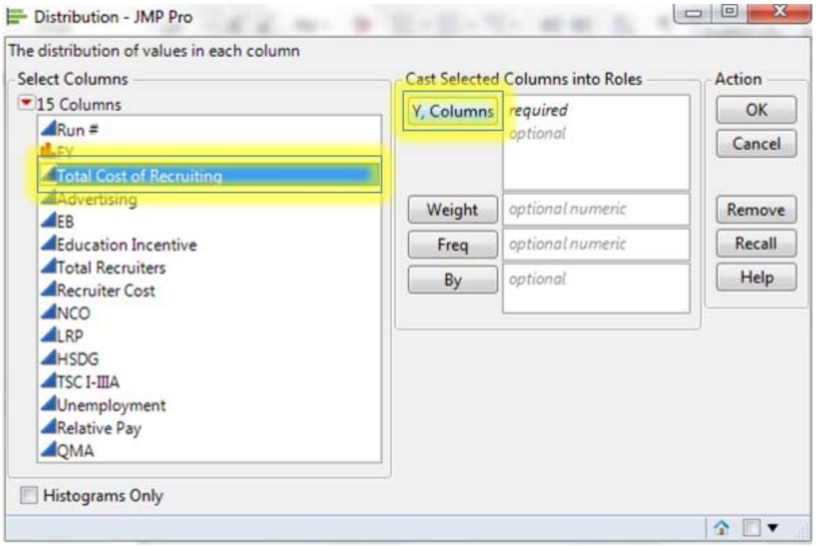
The distribution of the total cost of recruiting for FY 2017 is explored. This technique can be applied to any of the output variables to better understand its distribution and possible spread values.



Step 1: Select "Analyze" from the ribbon, and select "Distribution" from the drop down menu.

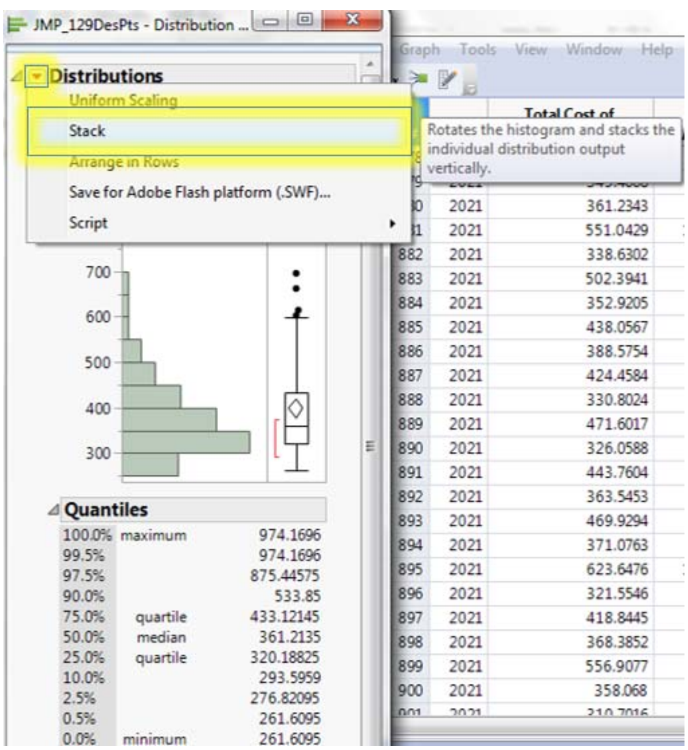


Step 2: Select "Total Cost of Recruiting" from the list of columns, and click on the "Y, Columns" button.



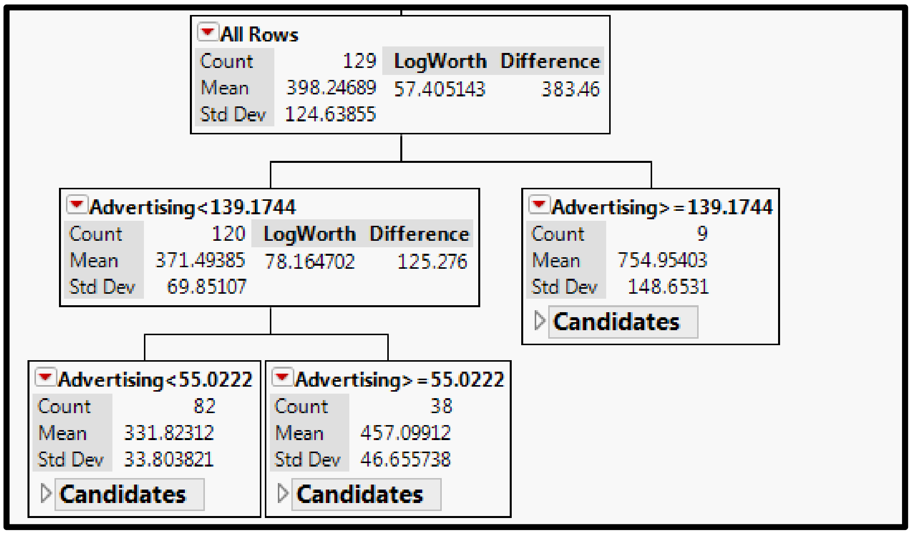
The distribution for Total Cost of Recruiting will appear.

Step 3: To rotate the distribution to appear horizontal, click on the red triangle in the upper left hand corner of the graph, and select "Stack" from the drop down menu.

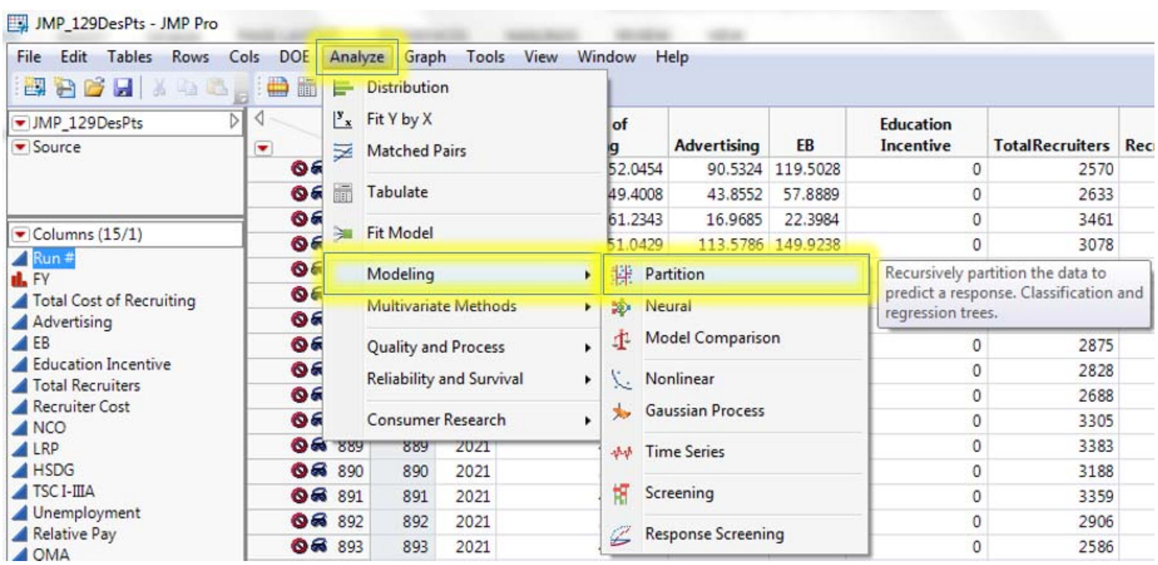


E. PARTITION TREES

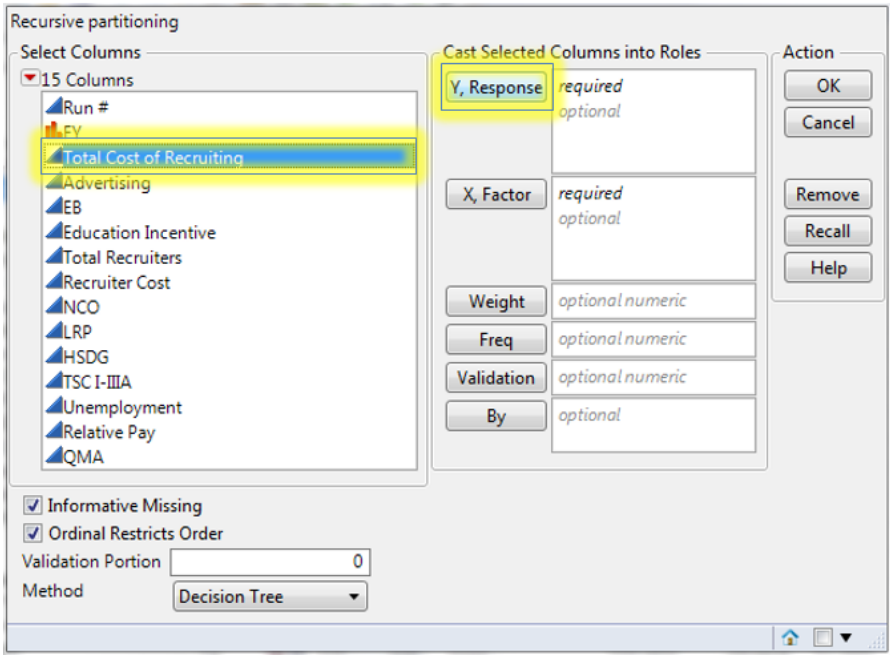
The partition tree on total cost of recruiting will be explored. The partition tree is a useful method that can help provide insights into variable interactions.



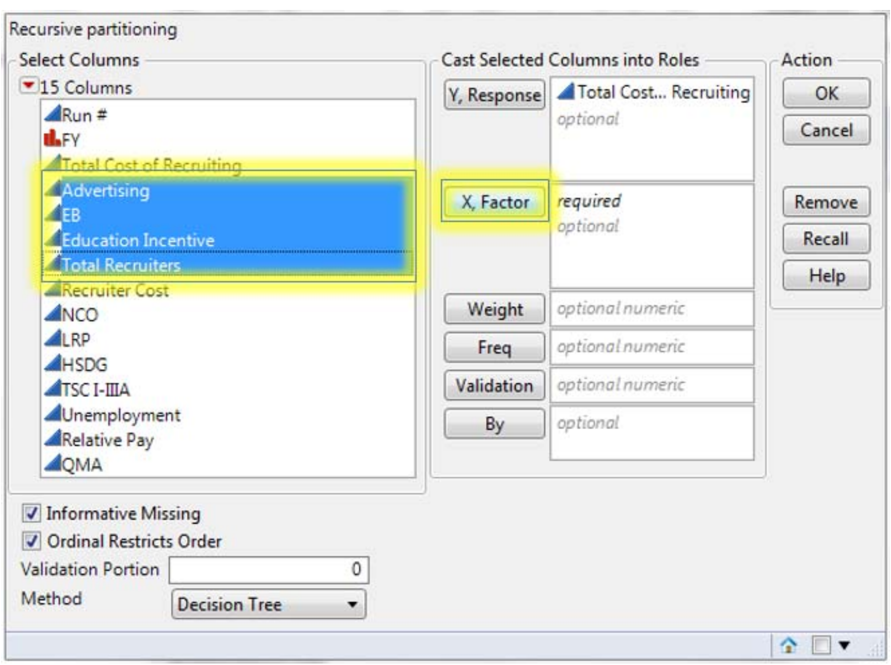
Step 1: To create a partition tree, select "Analyze" from the ribbon. Then choose "Modeling," and "Partition" from the drop down menus.



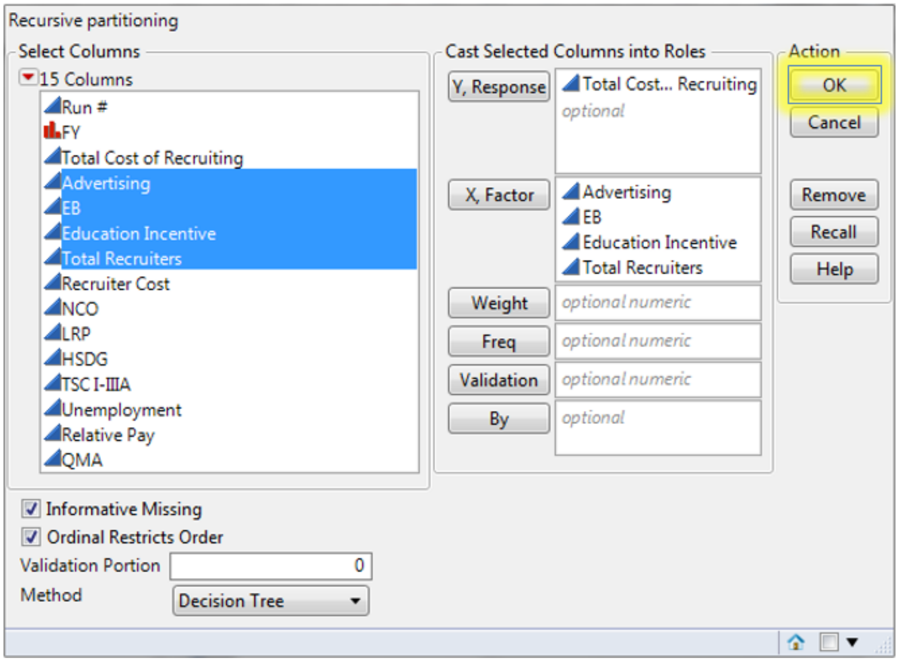
Step 2: Select “Total Cost of Recruiting” from the list of columns, and click on the “Y, Response” button.



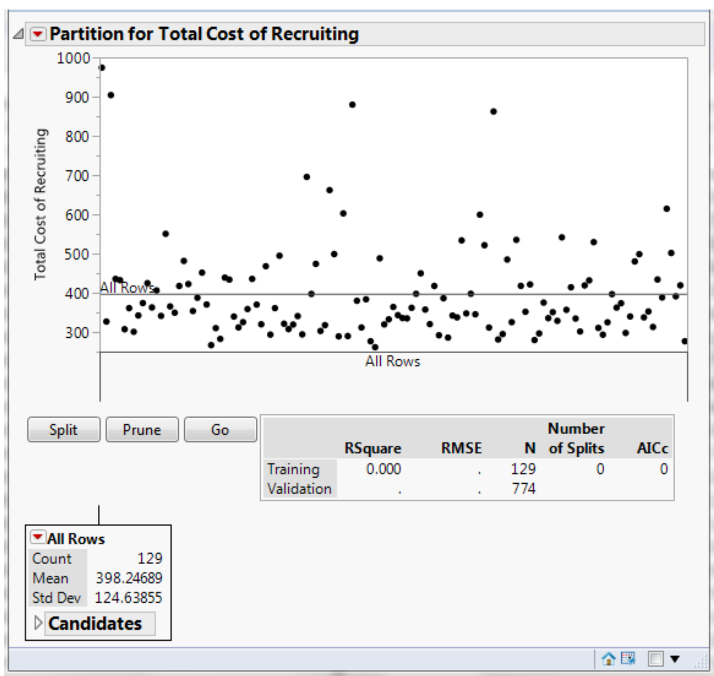
Step 3: Select each decision variable (Advertising, EB, Education Incentive, Total Recruiters) from the list of columns, then click on the “X, Factor” button.



Step 4: Click on the "OK" button.



The partition tree window will pop-up with just the parent node.



Step 5: To make the first split on "Total Cost of Recruiting," click on the "Split" button.

	RSquare	RMSE	N	Number of Splits	AICc
Training	0.619	76.624698	129	1	1491.72
Validation	0.607	78.407532	774		

All Rows

		LogWorth	Difference
Count	129		
Mean	398.24689	57.405143	383.46
Std Dev	124.63855		

Advertising<139.1744

Count	120
Mean	371.49385
Std Dev	69.85107

Candidates

Advertising>=139.1744

Count	9
Mean	754.95403
Std Dev	148.6531

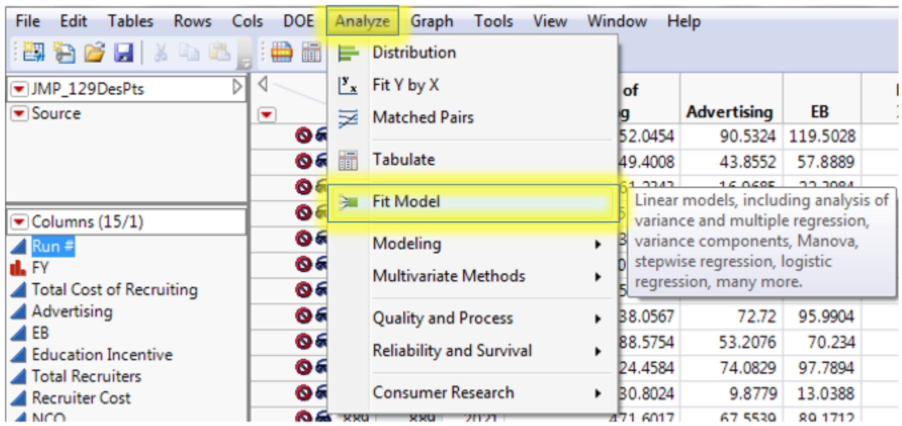
Candidates

Continue to split, by clicking the "Split" button. If you want to undo a split, click on the "Prune" button. A "Training" R^2 value of 0.80 is an adequate threshold to achieve. In this case, disregard the "Validation" R^2 value.

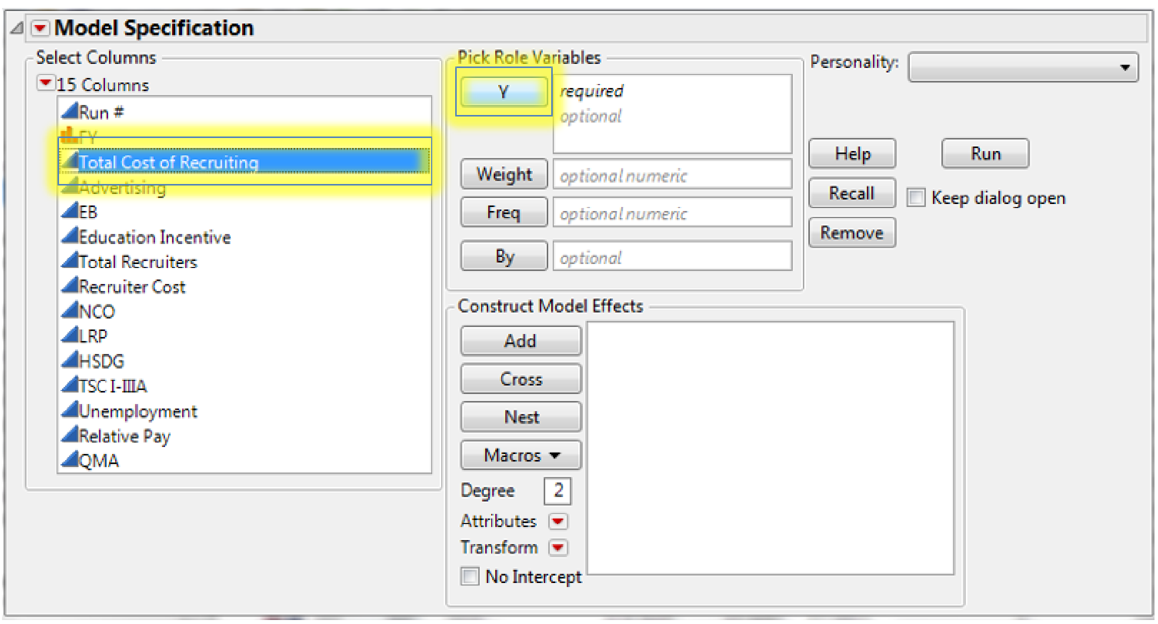
F. STEPWISE REGRESSION MODEL

To develop a model for the total cost of recruiting, stepwise regression is used to determine the beta estimates to fit a model.

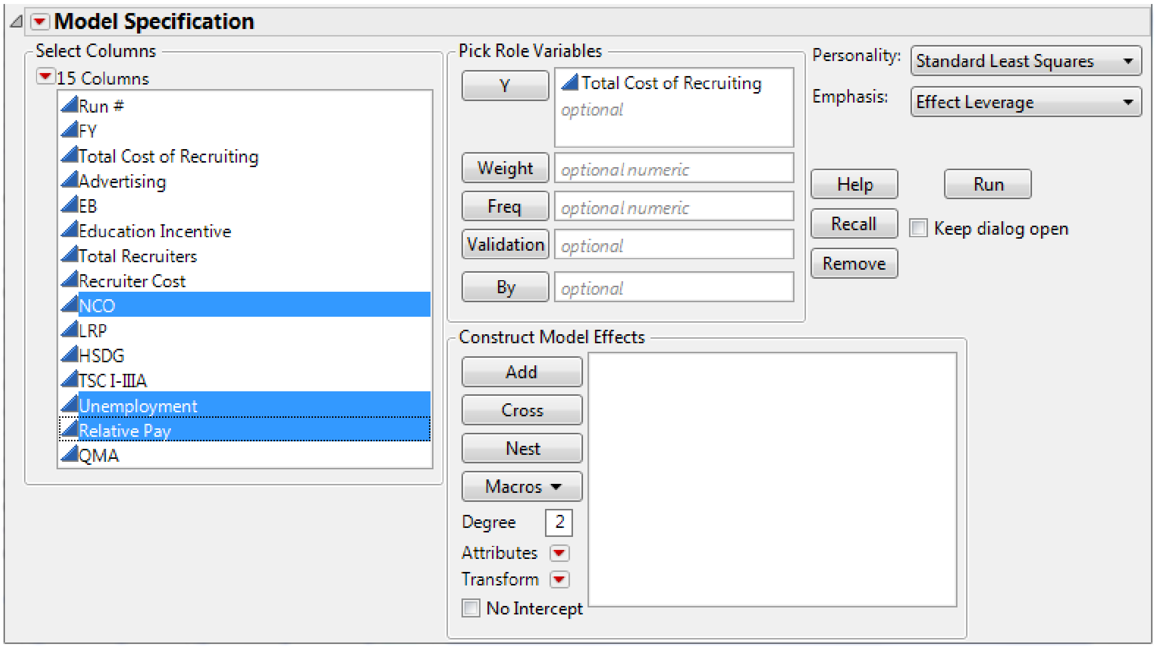
Step 1: Select "Analyze" from the ribbon, then "Fit Model" from the drop down menu.



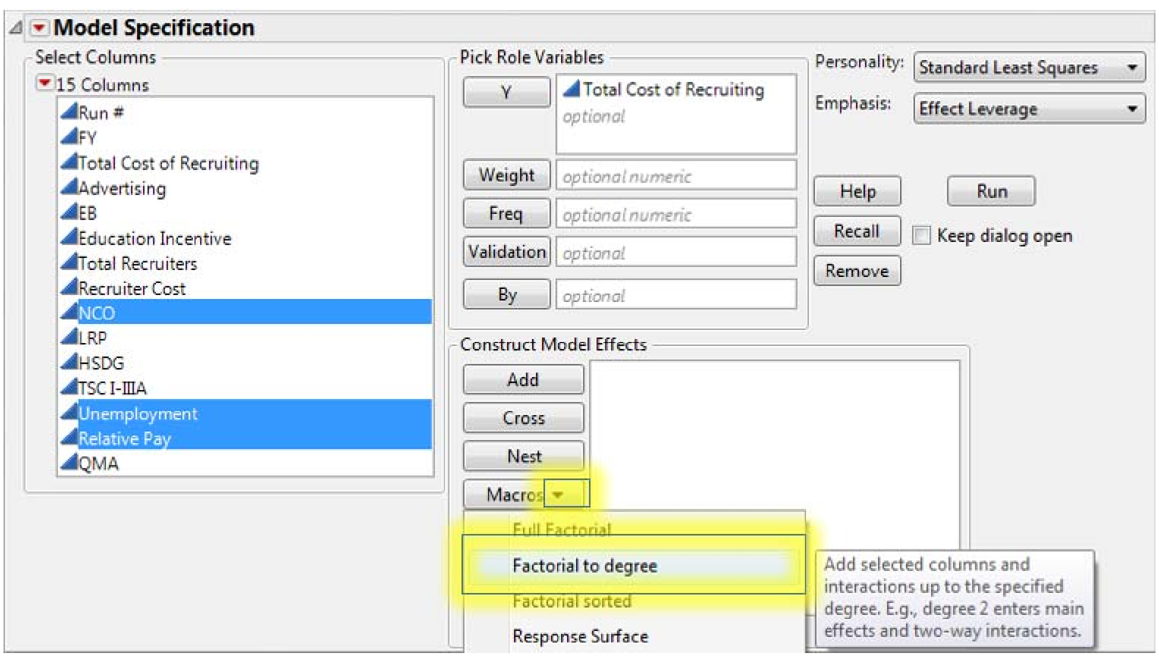
Step 2: Select "Total Cost of Recruiting" from the list of columns, and click on the "Y" button.



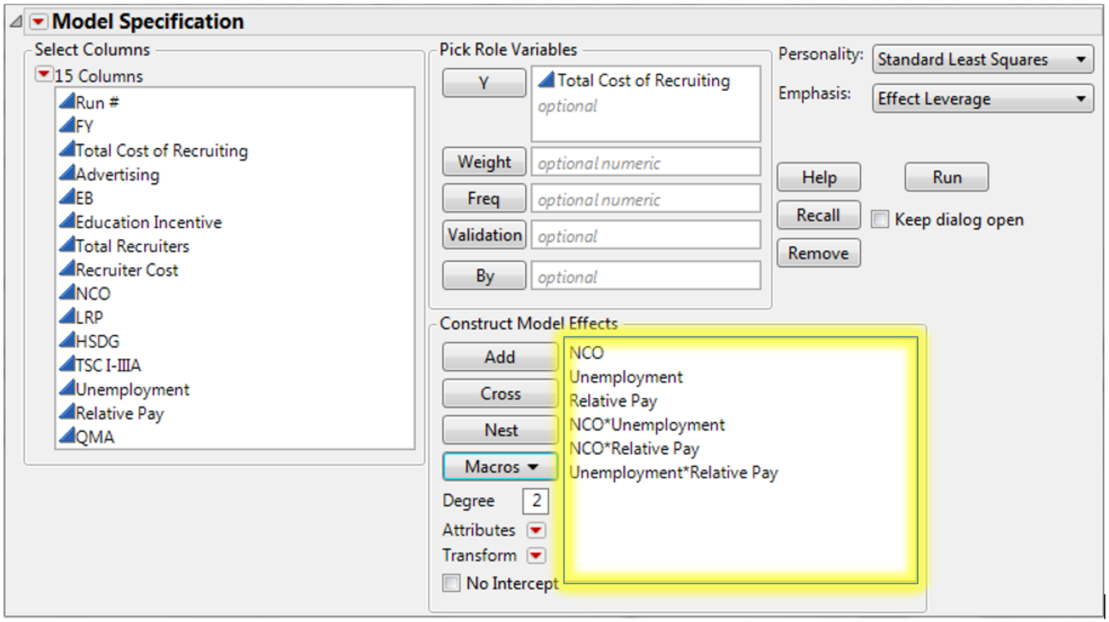
Step 3: While holding the Ctrl key, select each market factor that was varied in the PROM-WED excursion.



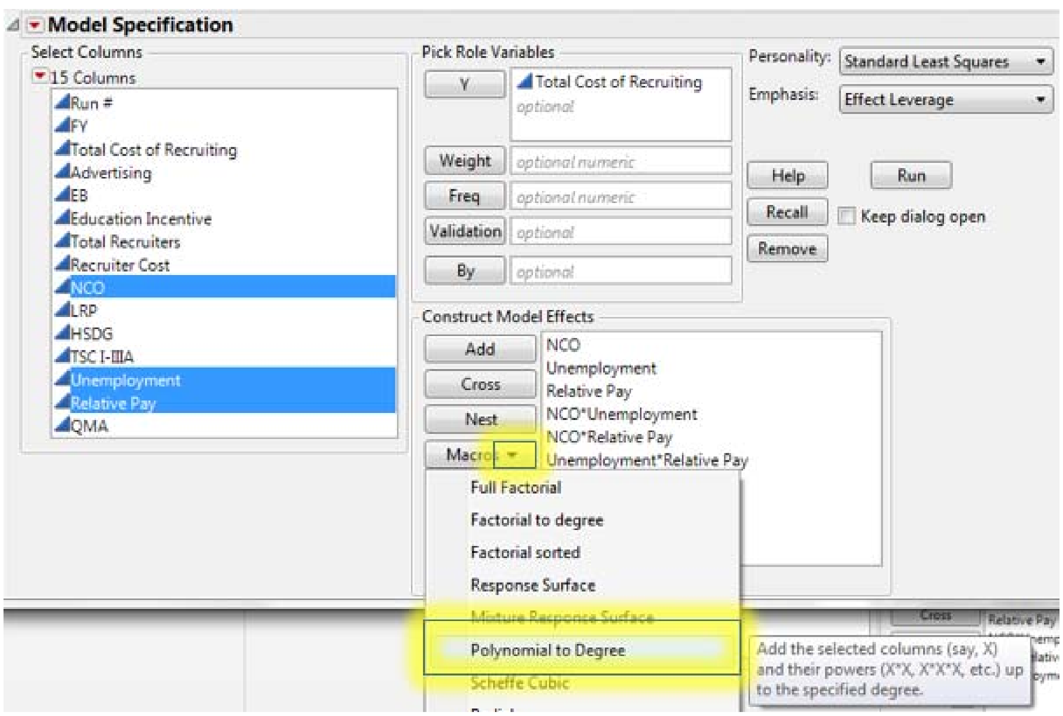
Select the right corner of the "Macros" button (i.e., the arrow), and select "Factorial to degree" from the drop-down menu.



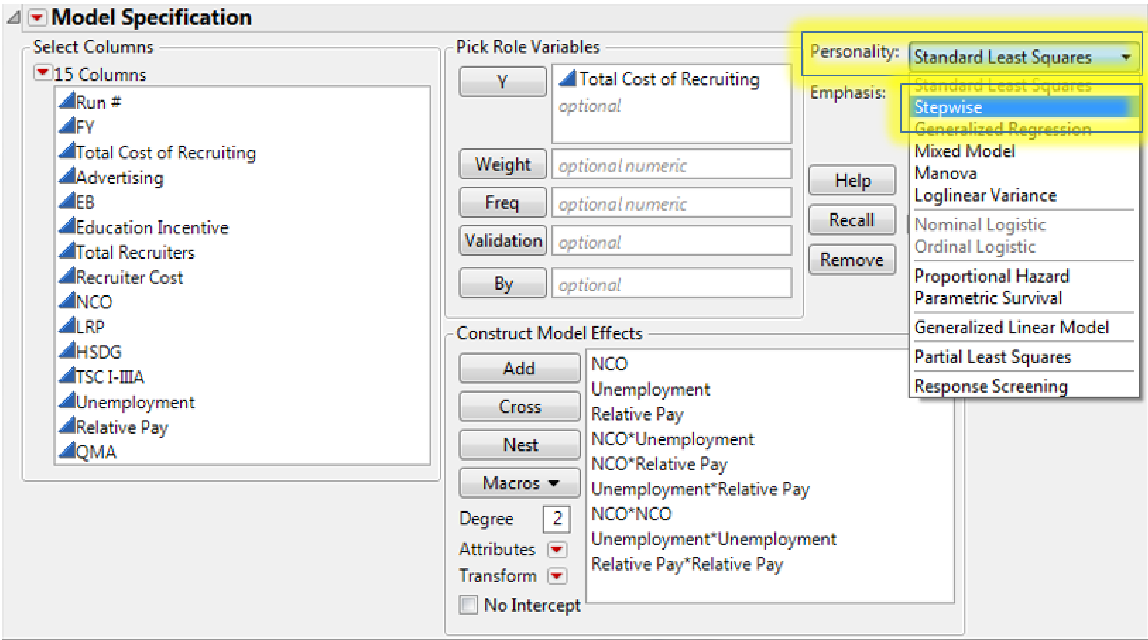
This will add all main effect and two-way interactions.



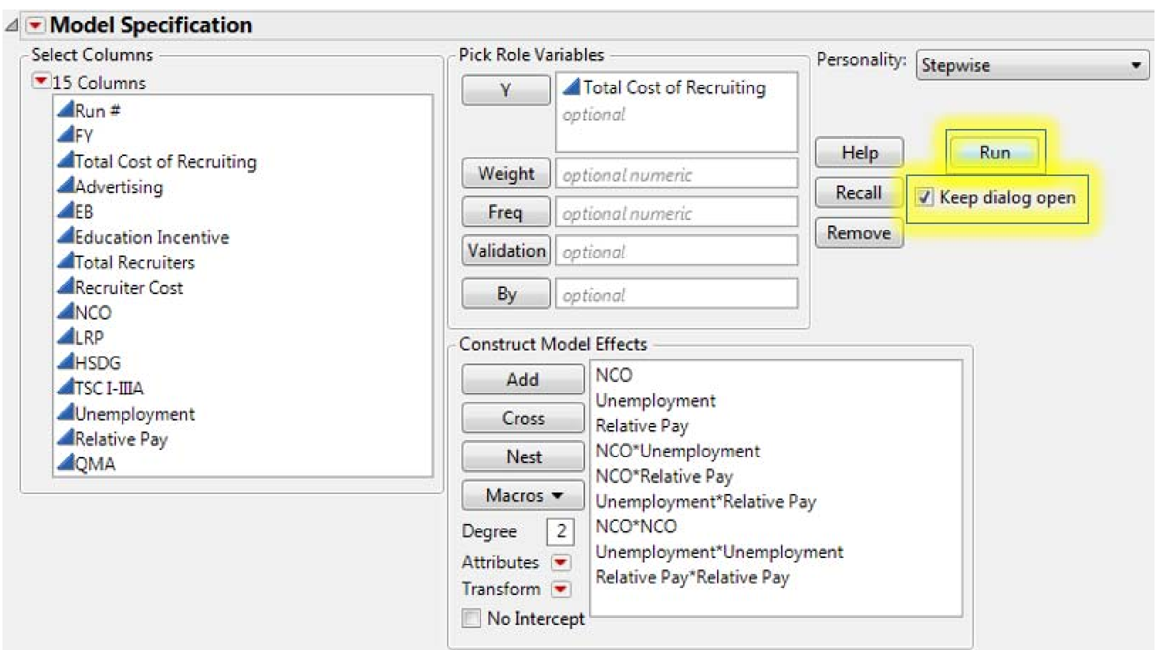
Again, while holding the Ctrl key, select each market factor that was varied in the PROM-WED excursion. Select the right corner of the "Macros" button (i.e., the arrow), and select "Polynomial to degree" from the drop-down menu. This will add all second degree polynomial interactions.



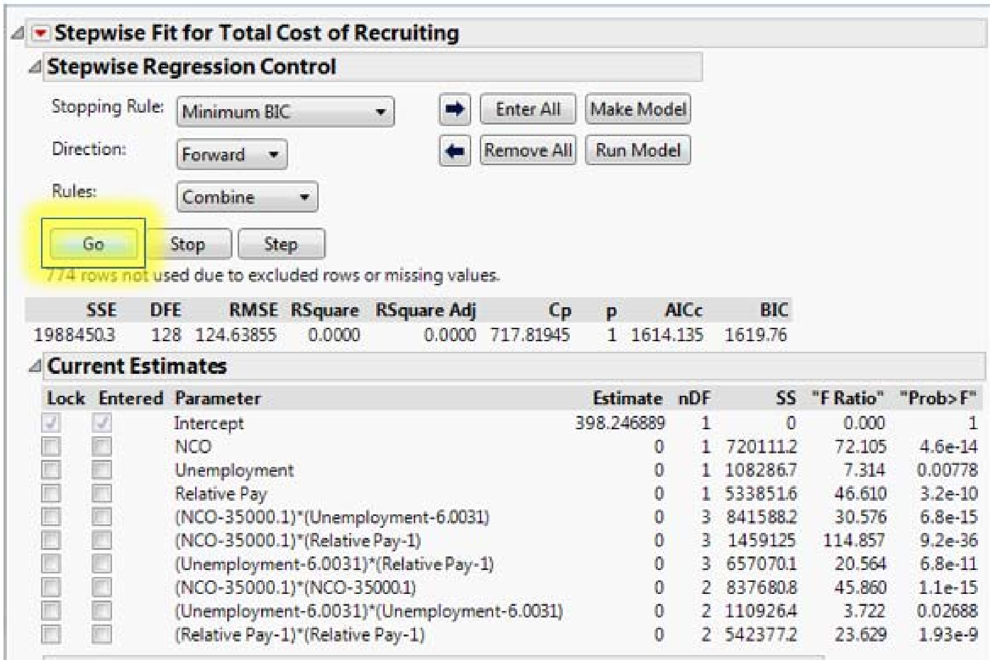
Step 4: From the "Personality" drop-down menu, select "Stepwise."



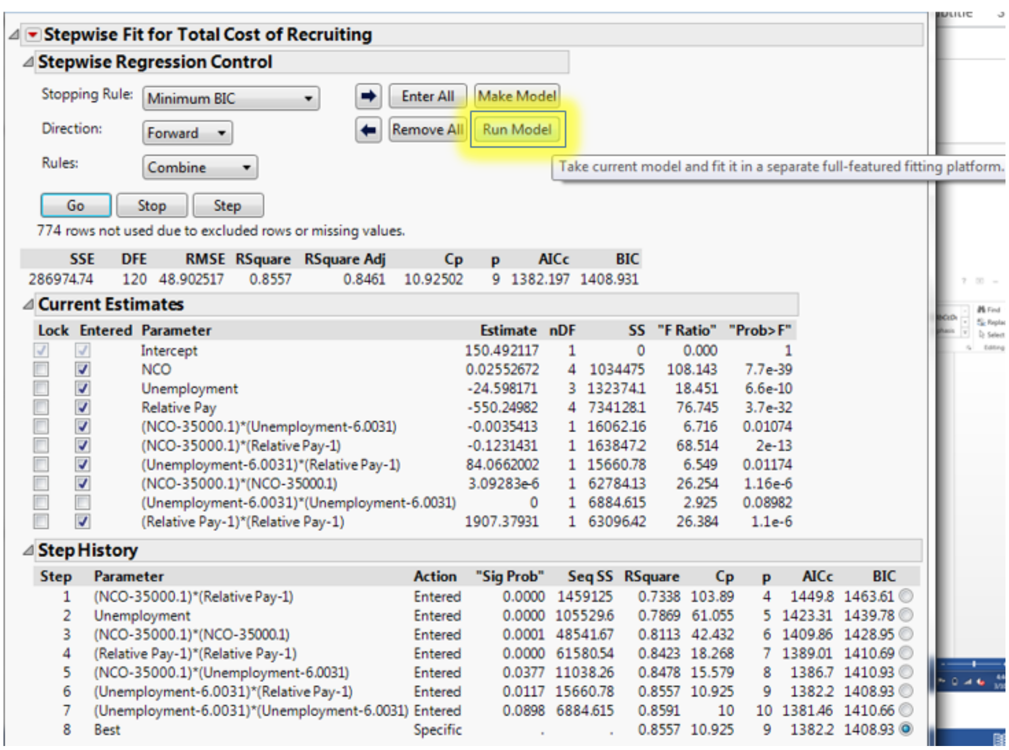
Step 5: Ensure that the "Keep dialog open" box is checked, and click the "Run" button.



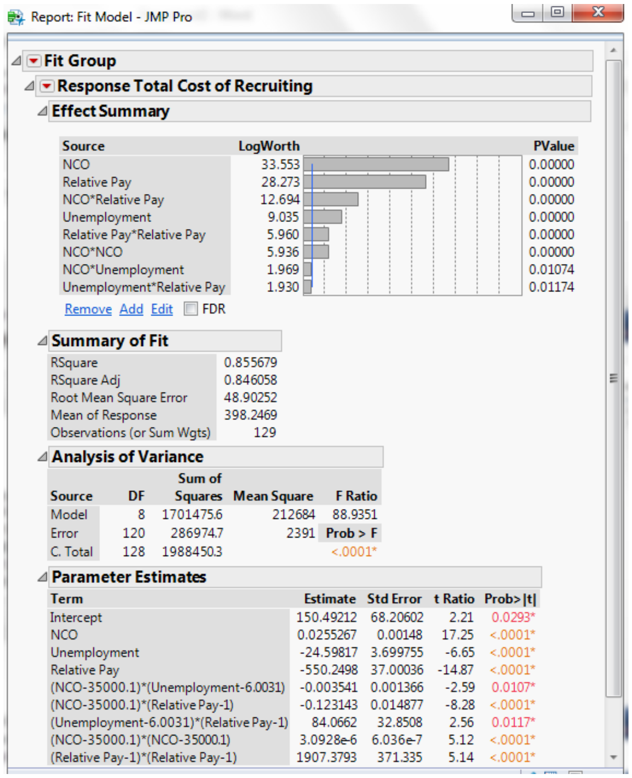
Step 6: The “Stepwise Regression Control” window will appear. Press the “Go” button.



Step 7: Once settled, select the “Run Model” button.



The “Report: Fit Model” window will appear.



Report: Fit Model - JMP Pro

Fit Group

Response Total Cost of Recruiting

Effect Summary

Source	LogWorth	PValue
NCO	33.553	0.00000
Relative Pay	28.273	0.00000
NCO*Relative Pay	12.694	0.00000
Unemployment	9.035	0.00000
Relative Pay*Relative Pay	5.960	0.00000
NCO*NCO	5.936	0.00000
NCO*Unemployment	1.969	0.01074
Unemployment*Relative Pay	1.930	0.01174

Remove Add Edit FDR

Summary of Fit

RSquare	0.855679
RSquare Adj	0.846058
Root Mean Square Error	48.90252
Mean of Response	398.2469
Observations (or Sum Wgts)	129

Analysis of Variance

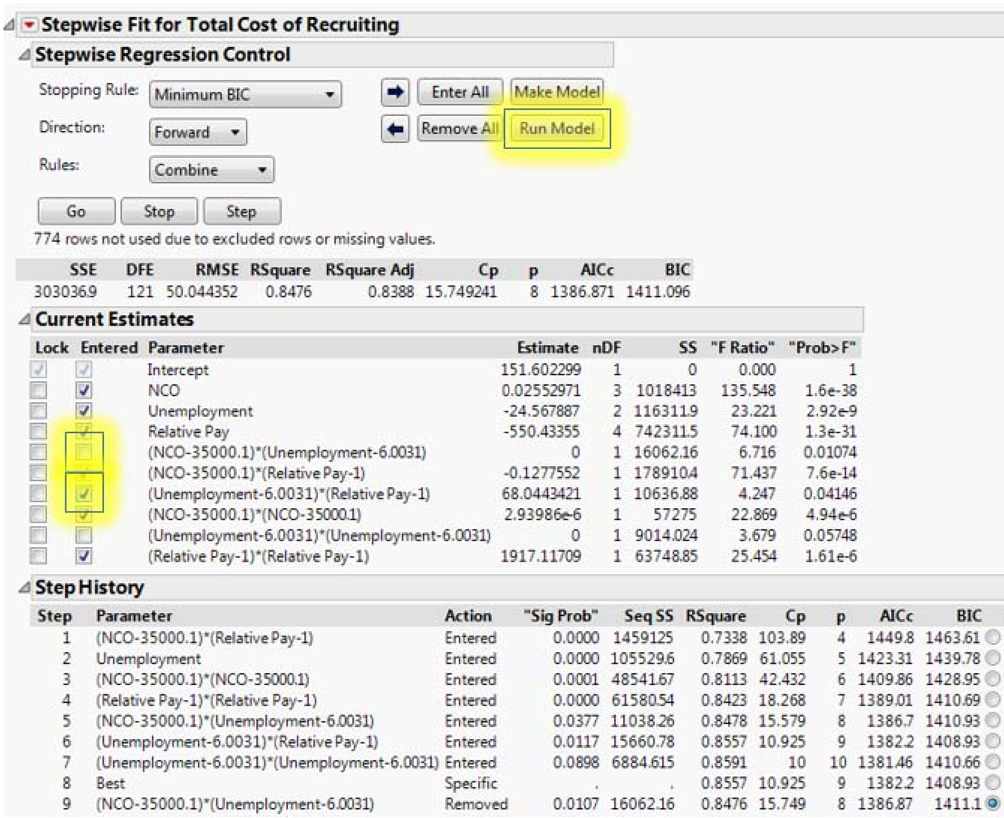
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	1701475.6	212684	88.9351
Error	120	286974.7	2391	Prob > F
C. Total	128	1988450.3		<.0001*

Parameter Estimates

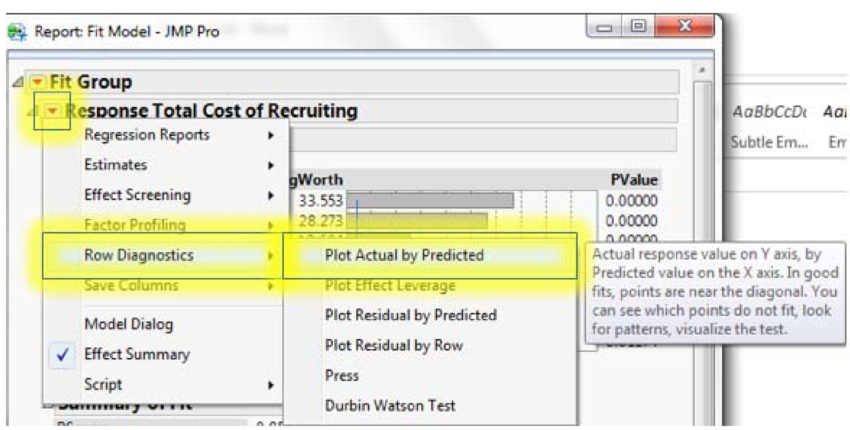
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	150.49212	68.20602	2.21	0.0293*
NCO	0.0255267	0.00148	17.25	<.0001*
Unemployment	-24.59817	3.699755	-6.65	<.0001*
Relative Pay	-550.2498	37.00036	-14.87	<.0001*
(NCO-35000.1)*(Unemployment-6.0031)	-0.003541	0.001366	-2.59	0.0107*
(NCO-35000.1)*(Relative Pay-1)	-0.123143	0.014877	-8.28	<.0001*
(Unemployment-6.0031)*(Relative Pay-1)	84.0662	32.8508	2.56	0.0117*
(NCO-35000.1)*(NCO-35000.1)	3.0928e-6	6.036e-7	5.12	<.0001*
(Relative Pay-1)*(Relative Pay-1)	1907.3793	371.335	5.14	<.0001*

At this point, you can decide if you would like to make manual adjustments to the stepwise regression. For example, the interactions between unemployment rate and relative pay, and the new accession mission and unemployment in this example both exhibit low “t Ratio” values.

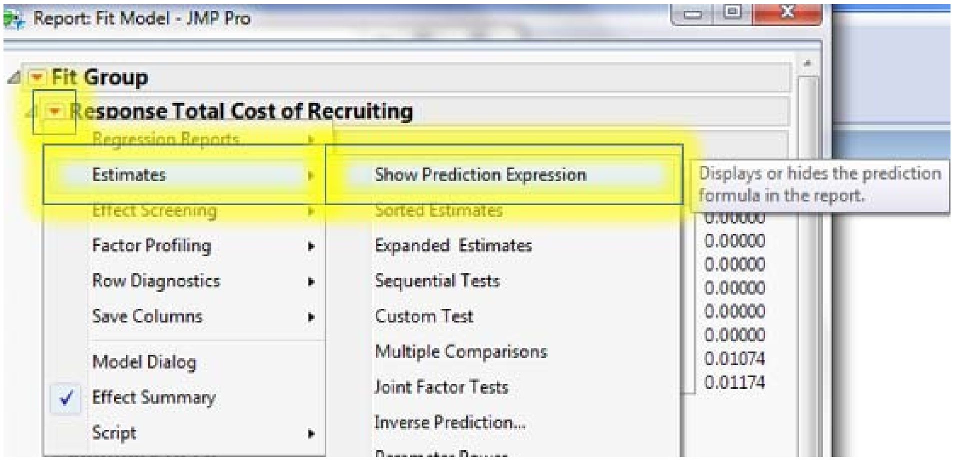
To remove these terms from the model, return to the “Stepwise Fit” window, and uncheck the terms in the “Entered” column that you would like to remove. Select “Run Model” to fit the new model.



Step 8: To graph the “Actual by Predicted” plot, select the red triangle next to “Response Total Cost of Recruiting.” From the drop-down menu, select “Row Diagnostics” and “Plot Actual by Predicted.”

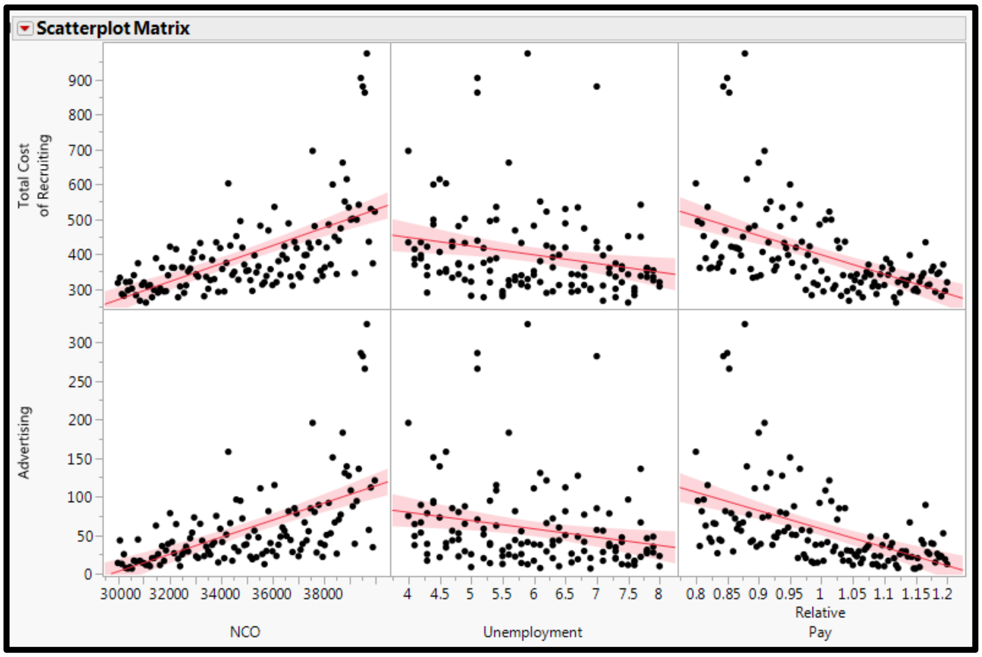


Step 9: To fit the prediction model, select the red triangle next to “Response Total Cost of Recruiting.” From the drop-down menu, select “Estimates” then “Show Prediction Expression.”

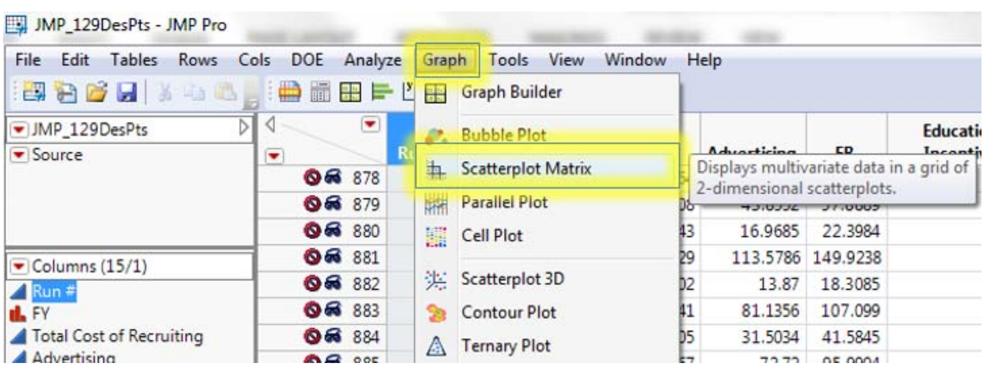


G. SCATTERPLOT MATRIX

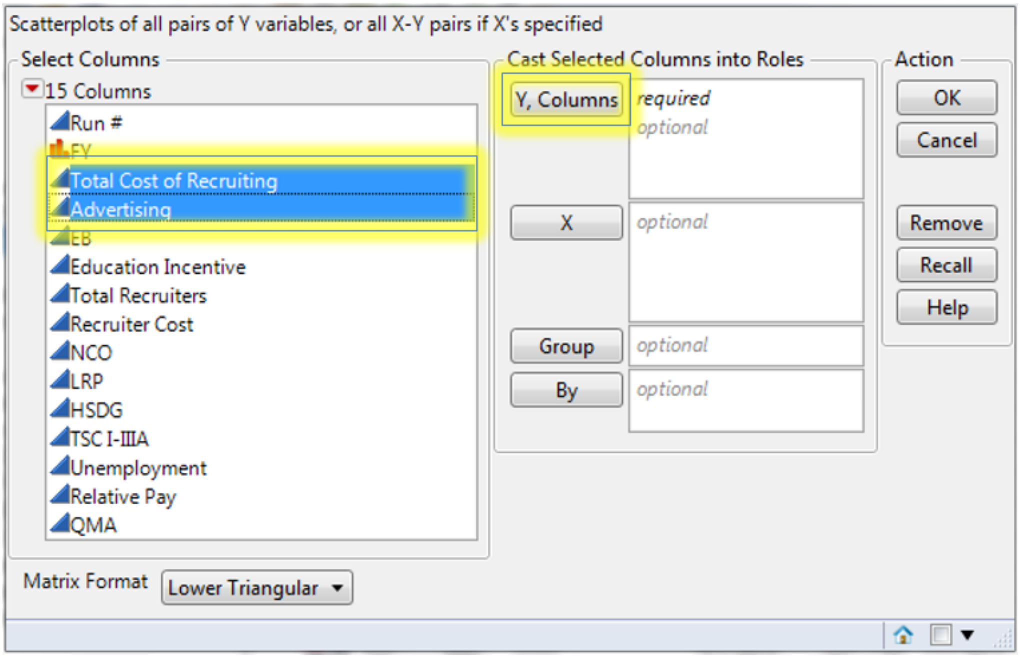
Scatterplot matrices can be used to visualize trends when multiple variables are changing.



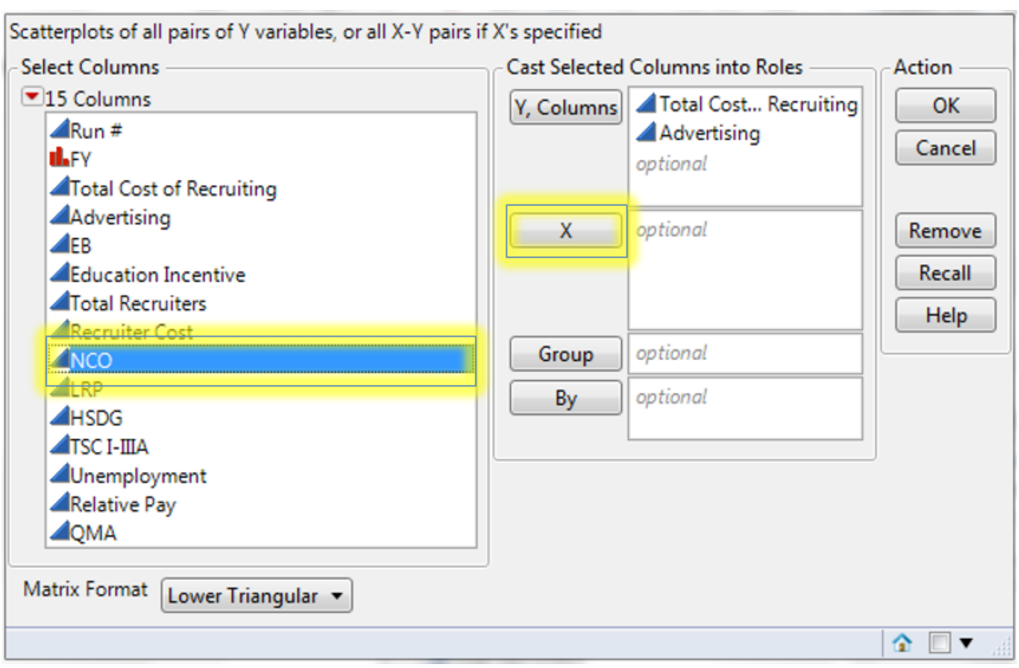
Step 1: Select "Graph" from the ribbon, then "Scatterplot Matrix" from the drop down menu.



Step 2: To set the Y-axis variables, select "Total Cost of Recruiting" and "Advertising" from the list of columns, and click on the "Y, Columns" button.

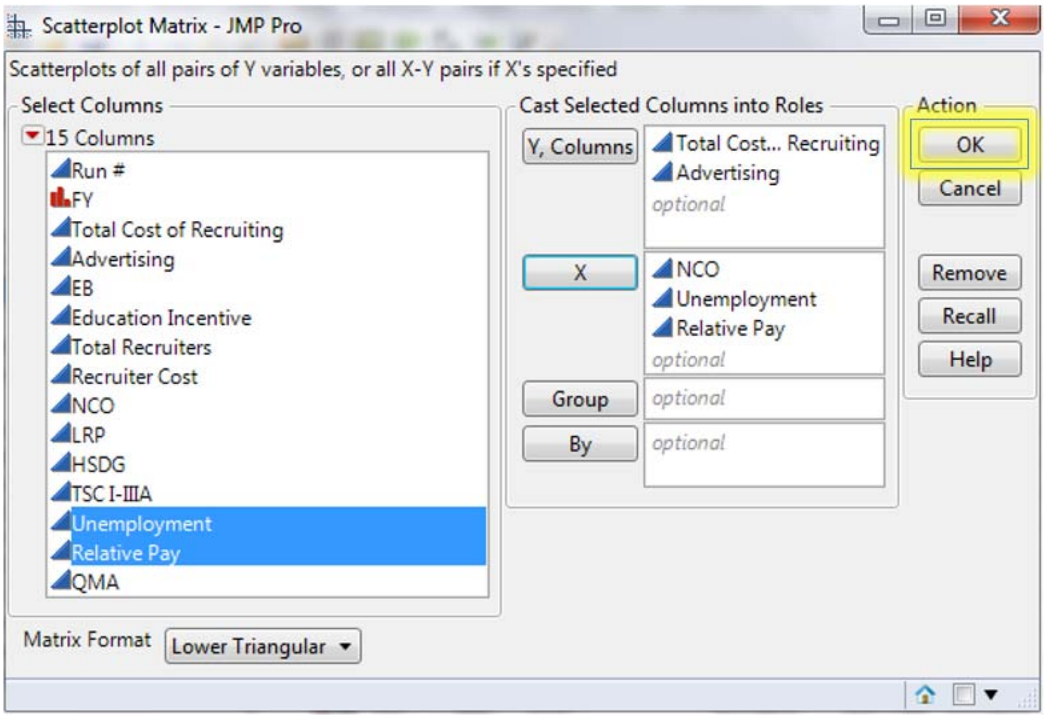


Step 3: To set the X-axis variables, select the variables of interest (NCO, Unemployment Rate and Relative Pay in this case), and click on the "X" button.

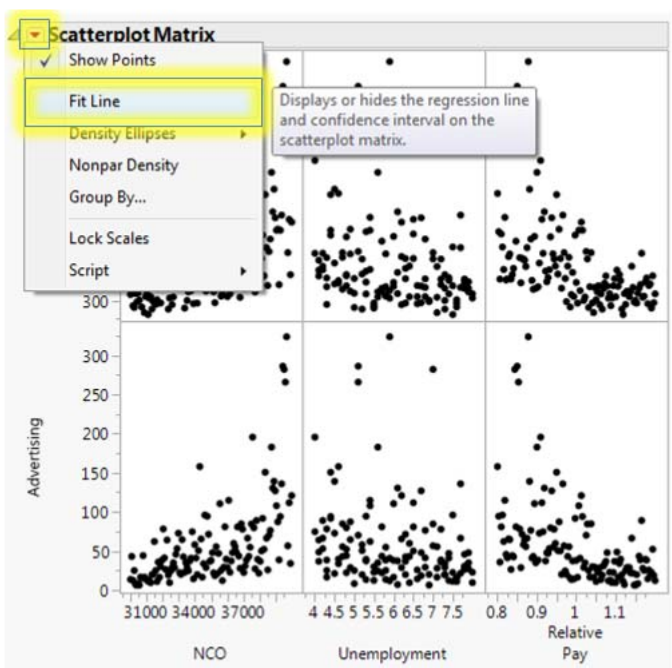


Step 4: Repeat Step 3 for Unemployment Rate and Relative Pay.

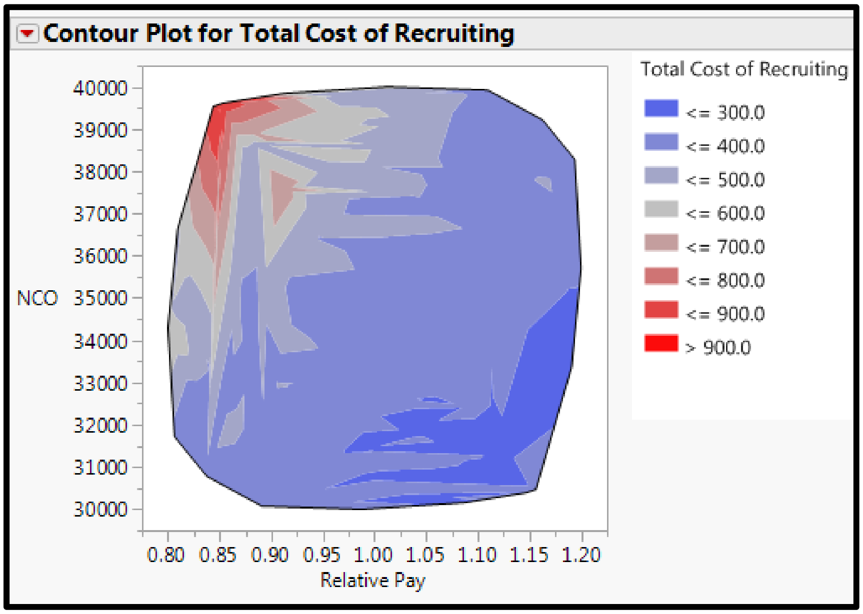
Step 5: To generate the scatterplot matrix, click the "OK" button.



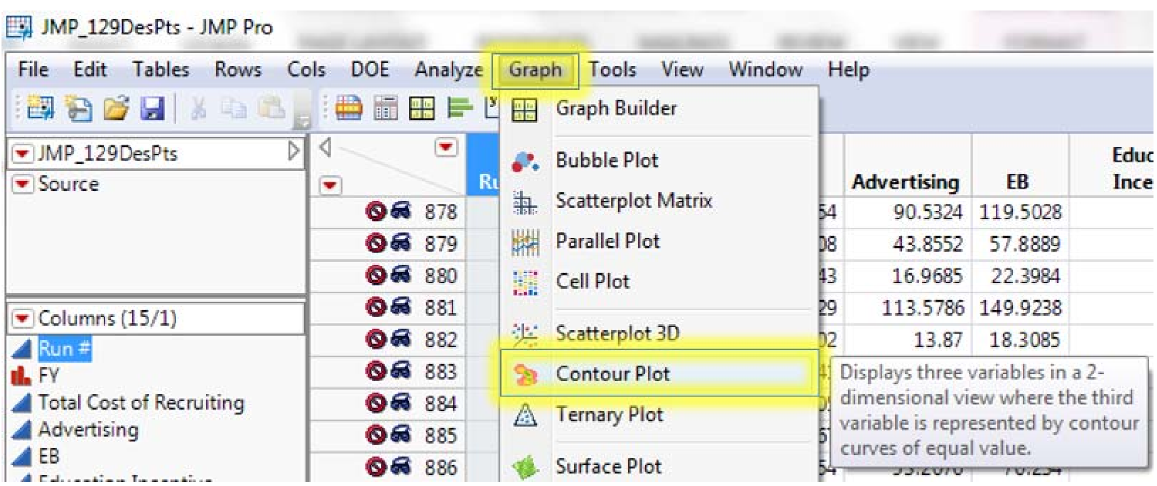
Step 6: To fit a trend line on the plots, click the red triangle, and select "Fit Line" from the drop down menu.



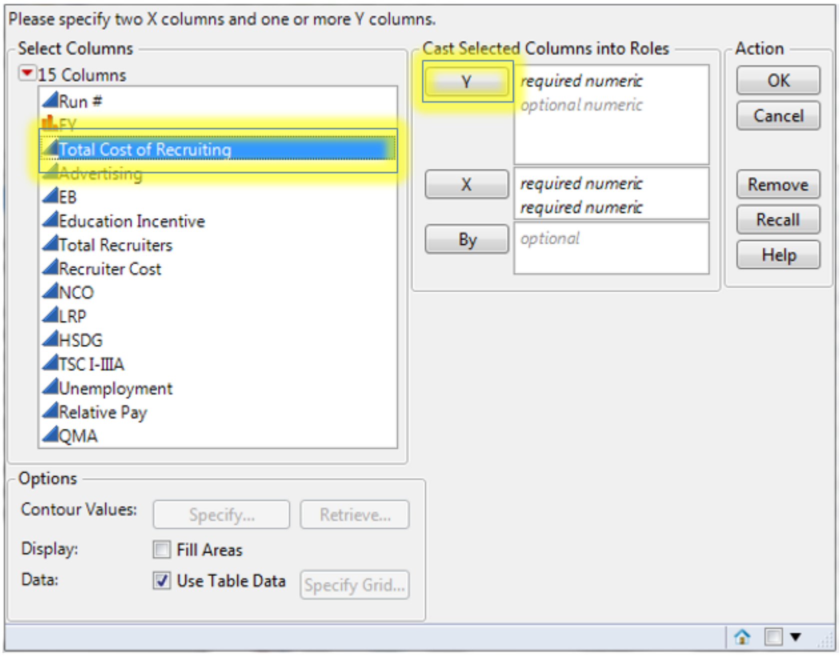
H. CONTOUR PLOTS



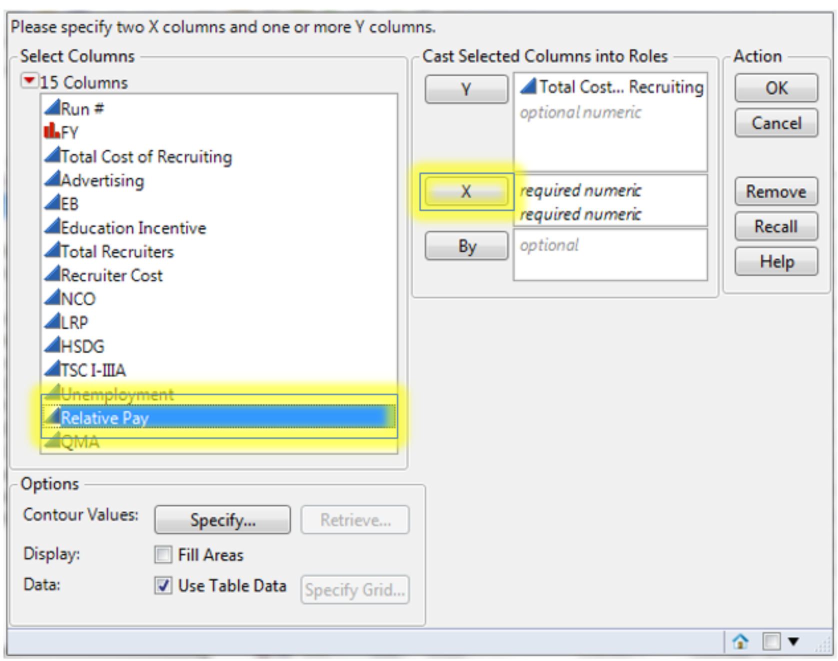
Step 1: Select "Graph" from the ribbon, then "Contour Plot" from the drop down menu.



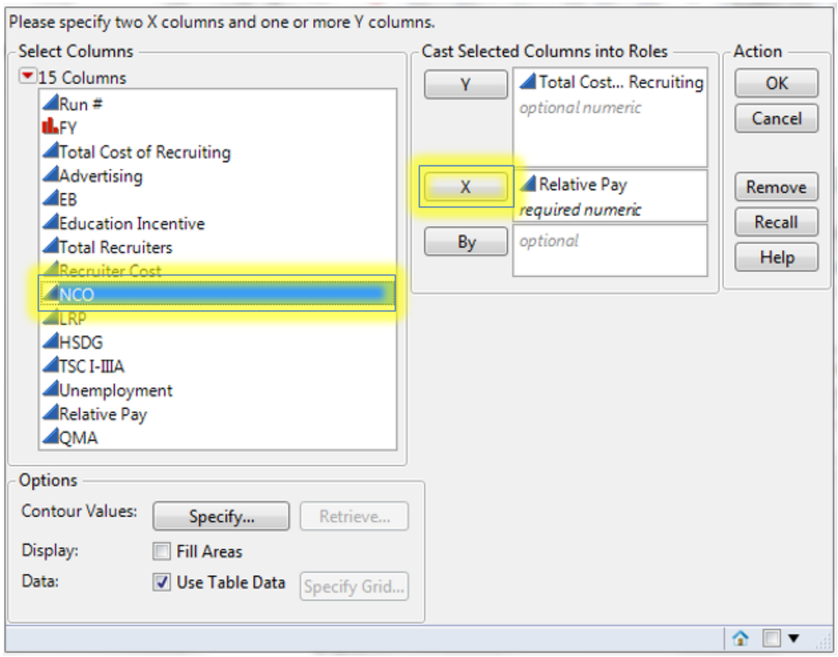
Step 2: To set “Total Cost of Recruiting” as the variable represented by the color scale, select “Total Cost of Recruiting” from the list of columns, and click the “Y” button.



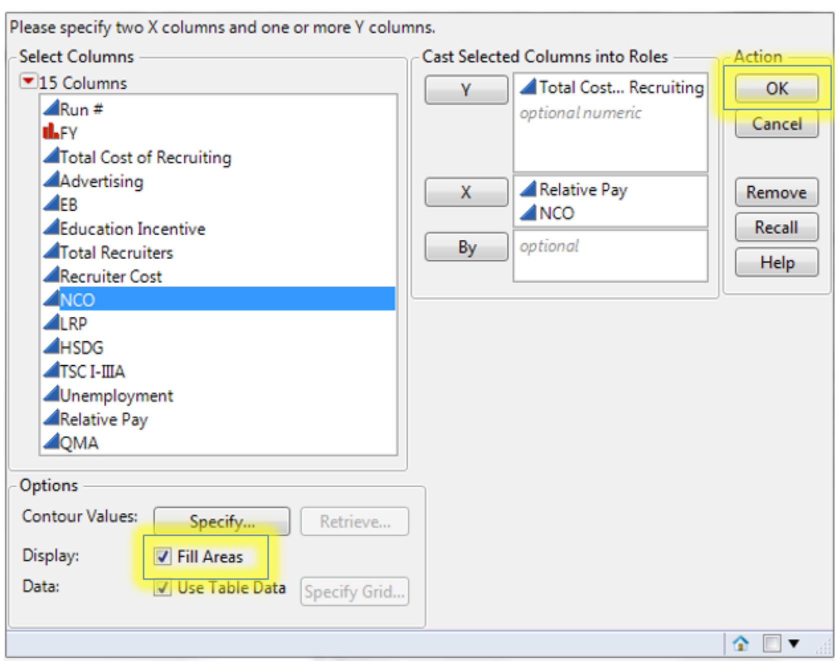
Step 3: To set “Relative Pay” as the x-axis, select “Relative Pay” from the list of columns, and click the “X” button.



Step 4: To set the new accession mission (NCO) as the y-axis, select "NCO" from the list of columns, and click the "X" button.



Step 5: Select the "Fill Areas" box, then click the "OK" button to generate the contour plot.



V. EXAMPLE TEST CASES

Two test case examples are provided to demonstrate PROM-WED's capabilities.

A. EFFECT OF ECONOMIC UNCERTAINTIES

What is the optimal allocation of recruiting resources that is robust to a broad range of economic uncertainties?

Variable Type	Variable Name	Value Low	Value High
Decision Variable	Recruiters	2,500 recruiters	3,500 recruiters
Market Factor	Unemployment Rate	4.0%	8.0%
Market Factor	Relative Pay	0.80	1.20
Policy Factor	Recruiting Mission (NCO)	30,000 recruits	40,000 recruits

B. EFFECT OF LEGALIZATION OF MARIJUANA TEST CASE:

What is the optimal allocation of recruiting resources if the Navy desires to increase the percentage of high quality recruits from 70 percent to 85 percent? Due to uncertainties in the current fiscal environment, the unemployment rate may fluctuate between 4 to 8 percent and the ratio of relative pay may vary between 0.8 and 1.2. In addition, since marijuana has been legalized for recreational use in many states nationwide, drug-use amongst 18–24 year-olds is expected to increase. An increase in drug-use means less young adults qualify for military service. This test case models the effect of an annual decrease of 10,000 qualified military available due to pre-service drug-use.

Variable Type	Variable Name	Value Low	Value High
Decision Variable	Production Recruiters	2,500 recruiters	3,500 recruiters
Market Factor	Unemployment Rate (UE)	4.0%	8.0%
Market Factor	Percentage of High Quality Recruits (TSC I-III)	70%	85%
Market Factor	Relative Pay	0.8	1.2
Market Factor	Qualified Military Available (QMA)	*See Table 13	
Policy Factor	Recruiting Mission (NCO)	30,000 recruits	40,000 recruits

Cumulative Effect of Decrease in QMA

FY	QMA Value Low	QMA Value High
2015	1,873,304	1,883,304
2016	1,863,304	1,873,304
2017	1,853,304	1,863,304
2018	1,843,304	1,853,304
2019	1,833,304	1,843,304
2020	1,823,304	1,833,304
2021	1,813,304	1,823,304

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APPENDIX D. SCENARIO INPUT REPORTS

A. PARAMETER INPUTS FOR FIGURE 45

Where "Recruiters" is the only variable that is fixed. EB, NCF, and advertising are floated.

		2015	2016	2017	2018	2019	2020	2021
NCF	**high**	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	low	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
UE	**high**	0.08	0.08	0.08	0.08	0.08	0.08	0.08
	low	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Recruiters	**high**	3913	3913	3913	3913	3913	3913	3913
	low	3913	3913	3913	3913	3913	3913	3913
LRP	**high**	7.44	11.22	11.28	11.38	11.43	11.46	11.67
	low	7.44	11.22	11.28	11.38	11.43	11.46	11.67
Advertising	**high**	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264
	low	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264
EB	**high**	40.971	40.971	40.971	40.971	40.971	40.971	40.971
	low	40.971	40.971	40.971	40.971	40.971	40.971	40.971
NCO	**high**	35025	36425	36800	35800	35225	34650	34650
	low	35025	36425	36800	35800	35225	34650	34650
TSC	**high**	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	low	0.7	0.7	0.7	0.7	0.7	0.7	0.7
HSDG	**high**	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	low	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Rel Pay	**high**	1.2	1.2	1.2	1.2	1.2	1.2	1.2
	low	1.2	1.2	1.2	1.2	1.2	1.2	1.2
QMA	**high**	1883304	1883304	1883304	1883304	1883304	1883304	1883304
	low	1883304	1883304	1883304	1883304	1883304	1883304	1883304

B. PARAMETER INPUTS FOR FIGURE 46

Where "Recruiters" is the only variable that is fixed. EB, NCF, and advertising are floated.

		2015	2016	2017	2018	2019	2020	2021
NCF	**high**	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	Low	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
UE	**high**	0.08	0.08	0.08	0.08	0.08	0.08	0.08
	Low	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Recruiters	**high**	3500	3500	3500	3500	3500	3500	3500
	Low	2500	2500	2500	2500	2500	2500	2500
LRP	**high**	7.44	11.22	11.28	11.38	11.43	11.46	11.67
	Low	7.44	11.22	11.28	11.38	11.43	11.46	11.67
Advertising	**high**	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264
	Low	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264
EB	**high**	40.971	40.971	40.971	40.971	40.971	40.971	40.971
	Low	40.971	40.971	40.971	40.971	40.971	40.971	40.971
NCO	**high**	35025	36425	36800	35800	35225	34650	34650
	Low	35025	36425	36800	35800	35225	34650	34650
TSC	**high**	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Low	0.7	0.7	0.7	0.7	0.7	0.7	0.7
HSDG	**high**	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	Low	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Rel Pay	**high**	1.2	1.2	1.2	1.2	1.2	1.2	1.2
	Low	1.2	1.2	1.2	1.2	1.2	1.2	1.2
QMA	**high**	1883304	1883304	1883304	1883304	1883304	1883304	1883304
	Low	1883304	1883304	1883304	1883304	1883304	1883304	1883304

C. PARAMETER INPUTS FOR TEST CASE 1

Where "Recruiters" is the only variable that is fixed. EB, NCF, and advertising are floated.

		2015	2016	2017	2018	2019	2020	2021
NCF	**high**	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	Low	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
UE	**high**	0.08	0.08	0.08	0.08	0.08	0.08	0.08
	Low	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Recruiters	**high**	3500	3500	3500	3500	3500	3500	3500
	Low	2500	2500	2500	2500	2500	2500	2500
LRP	**high**	7.44	11.22	11.28	11.38	11.43	11.46	11.67
	Low	7.44	11.22	11.28	11.38	11.43	11.46	11.67
Advertising	**high**	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264
	Low	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264
EB	**high**	40.971	40.971	40.971	40.971	40.971	40.971	40.971
	Low	40.971	40.971	40.971	40.971	40.971	40.971	40.971
NCO	**high**	40000	40000	40000	40000	40000	40000	40000
	Low	30000	30000	30000	30000	30000	30000	30000
TSC	**high**	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Low	0.7	0.7	0.7	0.7	0.7	0.7	0.7
HSDG	**high**	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	Low	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Rel Pay	**high**	1.2	1.2	1.2	1.2	1.2	1.2	1.2
	Low	0.8	0.8	0.8	0.8	0.8	0.8	0.8
QMA	**high**	1883304	1883304	1883304	1883304	1883304	1883304	1883304
	Low	1883304	1883304	1883304	1883304	1883304	1883304	1883304

D. PARAMETER INPUTS FOR TEST CASE 2

Where "Recruiters" is the only variable that is fixed. EB, NCF, and advertising are floated.

		2015	2016	2017	2018	2019	2020	2021
NCF	high	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	Low	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
UE	high	0.08	0.08	0.08	0.08	0.08	0.08	0.08
	Low	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Recruiters	high	3500	3500	3500	3500	3500	3500	3500
	Low	2500	2500	2500	2500	2500	2500	2500
LRP	high	7.44	11.22	11.28	11.38	11.43	11.46	11.67
	Low	7.44	11.22	11.28	11.38	11.43	11.46	11.67
Advertising	high	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264
	Low	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264	34.8264
EB	high	40.971	40.971	40.971	40.971	40.971	40.971	40.971
	Low	40.971	40.971	40.971	40.971	40.971	40.971	40.971
NCO	high	40000	40000	40000	40000	40000	40000	40000
	Low	30000	30000	30000	30000	30000	30000	30000
TSC	high	0.85	0.85	0.85	0.85	0.85	0.85	0.85
	Low	0.7	0.7	0.7	0.7	0.7	0.7	0.7
HSDG	high	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	Low	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Rel Pay	high	1.2	1.2	1.2	1.2	1.2	1.2	1.2
	Low	0.8	0.8	0.8	0.8	0.8	0.8	0.8
QMA	high	1883304	1873304	1863304	1853304	1843304	1833304	1823304
	Low	1873304	1863304	1853304	1843304	1833304	1823304	1813304

APPENDIX E. SCENARIO OF INTEREST TO N1

The original baseline scenario request for a PROM-WED run was:

For your baseline scenario we can use the

- *Current program of record for Recruiting mission is about 34000, so use: 30000 - 40000*
- *Advert: $60M so use $40M - $100M*
- *EB: $55M - 80M range*
- *Recruiters (use Current onboard) I think they are at about 2900 so use 2500 – 3500*
- *Unemployment rate we use national rate and forecast per the Blue Chip Economic Indicators long range forecast. Which has current UE at ~5.0% so use (4.0% - 8.0%)*
- *Vary relative pay between .8 and 1.2*

(Palmer, personal communication, 14 Sep 2016)

Following continued communication with N1, the baseline scenario transitioned into a best case, worst case, and most likely case exploration. The following scenarios originated from that request. Test Case 1 and 2, explored within the report, combines all three of these cases into one PROM-WED run.

A. BEST CASE

The Navy's best case scenario would be a low recruiting mission, no limitation on the number of recruiters in the field, and favorable economic conditions for recruiting (i.e., high unemployment rate and relative pay favoring the military versus the civilian sector). Table 17 shows the variables that this scenario focuses on. In this case, all decision variables will be optimized.

Table 17. Scenario of Interest: Best Case

Variable Type	Variable Name	Value Low	Value High
Decision Variable	Recruiters	Float	
Market Factor	Recruiting Mission (NCO)	30,000 recruits	
Market Factor	Relative Pay	1.00	1.20
Market Factor	Unemployment Rate	5.5%	8.0%

B. WORST CASE

The Navy's worst case scenario would be a high recruiting mission, a limited number of recruiters in the field, and an economic environment that is unfavorable to recruiting (i.e., the unemployment rate is low and the relative pay favors the civilian sector). The inputs for the worst case scenario are shown in Table 18. In this case, the number of recruiters is fixed and all other decision variables will be optimized.

Table 18. Scenario of Interest: Worst Case

Variable Type	Variable Name	Value Low	Value High
Decision Variable	Recruiters	2,500 recruiters	
Market Factor	Recruiting Mission (NCO)	40,000 recruits	
Market Factor	Relative Pay	0.80	1.00
Market Factor	Unemployment Rate	4.0%	5.5%

C. MOST LIKELY

The most likely scenario that the Navy will face is a moderate recruiting mission, a limited range of available recruiters, and a balanced economic situation that naturally fluctuates between favorable and unfavorable conditions for recruiting. Table 19 shows the input variables for this scenario, where number of recruiters is fixed and tested over a range of values. All other decision variables will be optimized.

Table 19. Scenario of Interest: Most Likely

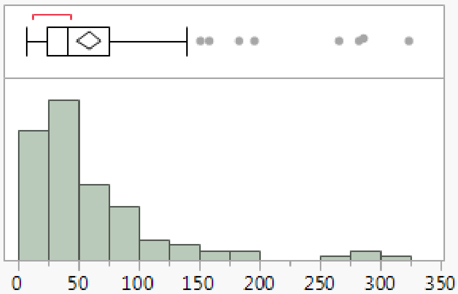
Variable Type	Variable Name	Value Low	Value High
Decision Variable	Recruiters	2,500 recruiters	3,000 recruiters
Market Factor	Recruiting Mission (NCO)	35,000 recruits	
Market Factor	Relative Pay	0.80	1.20
Market Factor	Unemployment Rate	4.5%	6.5%

APPENDIX F. DISTRIBUTIONS

A. FY 2017 DISTRIBUTIONS FOR TEST CASE 1

Distributions

Advertising



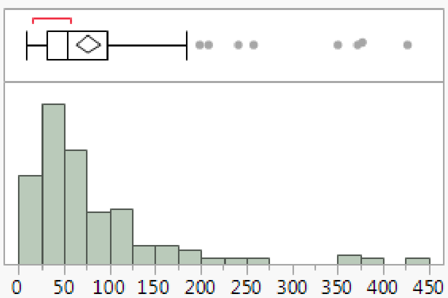
Quantiles

100.0%	maximum	323.6418
99.5%		323.6418
97.5%		278.0274
90.0%		120.9422
75.0%	quartile	73.9048
50.0%	median	39.7348
25.0%	quartile	22.92
10.0%		13.8271
2.5%		7.61005
0.5%		6.5819
0.0%	minimum	6.5819

Summary Statistics

Mean	58.118597
Std Dev	56.188302
Std Err Mean	4.9471041
Upper 95% Mean	67.907288
Lower 95% Mean	48.329906
N	129

EB



Quantiles

100.0%	maximum	427.2072
99.5%		427.2072
97.5%		366.996125
90.0%		159.6437
75.0%	quartile	97.5543
50.0%	median	52.4499
25.0%	quartile	30.2544
10.0%		18.2518
2.5%		10.0453
0.5%		8.6882
0.0%	minimum	8.6882

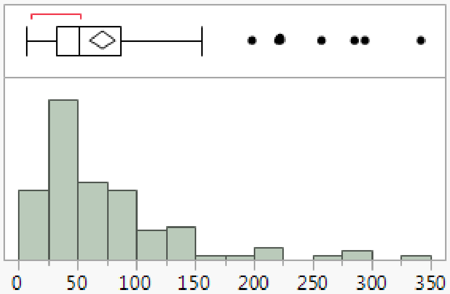
Summary Statistics

Mean	76.716542
Std Dev	74.168552
Std Err Mean	6.5301769
Upper 95% Mean	89.637612
Lower 95% Mean	63.795471
N	129

B. FY 2017 DISTRIBUTIONS FOR TEST CASE 2

Distributions

Advertising



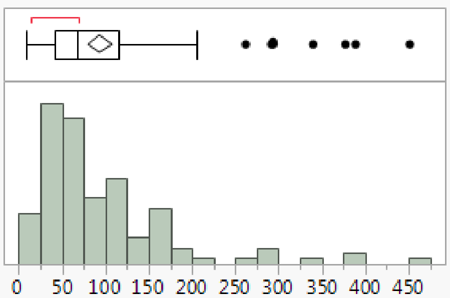
Quantiles

100.0%	maximum	342.3389
99.5%		342.3389
97.5%		278.834575
90.0%		131.319
75.0%	quartile	86.7565
50.0%	median	50.8824
25.0%	quartile	31.68145
10.0%		20.0803
2.5%		10.519725
0.5%		6.7331
0.0%	minimum	6.7331

Summary Statistics

Mean	71.101741
Std Dev	60.307798
Std Err Mean	5.3098056
Upper 95% Mean	81.608099
Lower 95% Mean	60.595384
N	129

EB



Quantiles

100.0%	maximum	451.8873
99.5%		451.8873
97.5%		368.061575
90.0%		173.341
75.0%	quartile	114.5186
50.0%	median	67.1648
25.0%	quartile	41.8195
10.0%		26.506
2.5%		13.88605
0.5%		8.8877
0.0%	minimum	8.8877

Summary Statistics

Mean	93.854303
Std Dev	79.606289
Std Err Mean	7.0089429
Upper 95% Mean	107.72269
Lower 95% Mean	79.985912
N	129

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